TURING AWARD SCIENTISTS: CONTRIBUTION AND RECOGNITION IN COMPUTER SCIENCE

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TURING AWARD SCIENTISTS: CONTRIBUTION AND RECOGNITION IN COMPUTER SCIENCE

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To my grandmother, Alexandra Fedorovna, and to those women and men who in their seemingly ordinary lives achieve extraordinary results

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LIST OF SYMBOLS AND ABBREVIATIONS

AAAI	American Association for Artificial Intelligence
ACL	Association for Computational Linguistics
ACM	Association for Processing Machinery
AEC	Atomic Energy Commission
AFIPS	American Federation of Information Processing Societies
AIEE	American Institute of Electrical Engineers
ASCC	Automatic Sequence Controlled Calculator
ASIS	American Society for Information Science
AT&T	American Telephone and Telegraph Company (Corporation)
Caltech	California Institute of Technology
CBI	Charles Babbage Institute
CMU	Carnegie Mellon University
CPCI-S	Conference Proceedings Citation Index- Science
CRA	Computing Research Association
CS	Computer Science
CST	Computer Sciences Theater Subcommittee of the ACM
DPMA	Data Processing Management Association
ECE	Electrical and Computer Engineering
ECSE	Experimental Computer Science and Engineering
EE	Electrical Engineering
EECS	Electrical Engineering and Computer Science
EWD	Abbreviation used by Edsger Wybe Dijkstra for manuscripts
IBM	International Business Machines Corporation
IEEE	Institute of Electrical and Electronics Engineers
IEEE-CG	Institute of Electrical and Electronics Engineers Computer Group
IPL	Information Processing Language
IRE	Institute of Radio Engineers
ISI	Institute for Scientific Information

ISI	Institute for Scientific Information
MIT	Massachusetts Institute of Technology
NCTM	National Council of Teachers of Mathematics
NCR	National Cash Register Company
NRC	National Research Council
NSF	National Science Foundation
OCLC	Online Computer Library Catalog
QCA	Qualitative Comparative Analysis
R&D	Research and Development
RCA	Radio Corporation of America (Company)
SCI	Simulation Council
UCLA	University of California in Los Angeles
U.S.	United States of America
USPTO	United States Patent and Trademark Office

SUMMARY

One of the most significant rewards in science is peer recognition, often bestowed in the form of awards. However, little is known about what sets apart award-winning contributions, how award committees determine prize-worthy contributions, and why some scientists are more likely to be recognized than others, particularly in the field of computer science. Using a mixed method approach that includes qualitative and quantitative techniques, this study investigates the characteristics of award-winning contributions, and the education and career factors associated with recipients of the Turing Award, a Nobel equivalent award in computer science, and compares them to those of a matched group of non-winning scientists. In regard to award-winning contributions, the study finds that the Turing Committee was just as likely to recognize contributions related to practice ("applied research") as to theory ("basic research"). In regard to education and career factors, the study reveals that neither scientific productivity nor the quality of contributions differentiated winning from non-winning scientists and their contributions. However, early advantages, visibility to the awarding association, prior eminence, and affiliation with a top computer science department distinguished award winners. These findings suggest that excellence in computer science is a quality that has not been defined, explained, or communicated by the award committee to the computing community or to the public. The findings call attention to the limitations of peer reviews and the importance of improving the design of nomination, evaluation, and selection procedures as well as citations accompanying the Turing Award and other computer science awards.

CHAPTER 1

INTRODUCTION

This study expands the understanding of scientific careers by examining the achievements and characteristics of a group of eminent computer scientists—recipients of the A. M. Turing Award, presented by the Association for Computing Machinery (ACM). The investigation principally covers the computing community in the United States from 1966 to 2008. The major aims of the study are to understand the characteristics of award-winning contributions and the method of selection of these contributions used by the Turing Committee that decides on the award, and to identify the educational and career factors that are associated with Turing Award winners, compared to non-winners. In addition, this study includes an overview of the formation, history, and nature of computing.

Achievement in science can be defined in multiple ways since scientists may devote a greater share of their efforts to one of their four principal roles: research, teaching, administration, and gate-keeping. Of these four roles, many scientists value the research role most highly[1] because it is "through originality, in greater or smaller increments, that knowledge advances" (Merton, 1973, p. 293). As a consequence, scientists are constantly reminded that "it is [their] role to advance knowledge and [their] happiest fulfillment of that role, to advance knowledge greatly" (Merton, 1973, p. 293). Not surprisingly, a contribution to a body of knowledge is also the strongest justification for recognition and the basis for the distribution of awards (Cole & Cole, 1973).[2] Recognition asserts property rights[3] in science and procures almost immediate fame that becomes a "symbol and reward for having done one's job well" (Merton, 1973, p. 294).

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[1] See Merton, 1973, p. 520.
[2] Public recognition and acknowledgement of originality in science also depends on establishing the priority of discovery, or being the "first" to bring the results into being (Merton, 1957/1973).
[3] By "property rights," Merton means "the recognition by others of the scientist's distinctive part in having brought the result into being" (Merton, 1973, p. 295).

One such symbol is recognition by the Turing Award, honoring contributions of "lasting and major technical importance to the computer field."[4]

Despite the importance of having contributions recognized, the factors that make some scientists more successful at being recognized are not evident, and are virtually unknown in the case of success in attaining a Turing Award. In the institution[5] of science, rewards are given for performance (Long & Fox, 1995; Merton, 1973; Parsons, 1951), and performance can be assessed through publication productivity, that is, the rate of publications (i.e., the number of publications per time period) and the quality of publications (i.e., the number of citations reflecting impact). If publication productivity were the only measure governing recognition in science, the process of evaluation would be relatively routinized, and the Institute for Scientific Information (ISI), now run by Thomson Reuters, would be able to predict Nobel Prize winners with accuracy (as they routinely attempt to do, see Brynko, 2010). However, the ISI has not been successful in making such predictions (Liu, 2005), suggesting that publication productivity and quality of publications are only part of what governs awards. Other factors apparently contribute to recognition in science. They need to be investigated and better understood.

RESEARCH QUESTIONS

For this study, recognition and success in computing are marked by the bestowing of the Turing Award, which creates two groups: Turing Award winners and a sample of non-winners, more precisely, 55 Turing Award winners (1966 – 2008) and 30 non-winners. Based on analysis of both groups, this study addresses two[6] main research questions:

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[4] This description of the award is listed on the ACM website. Retrieved December 5, 2007 from http://awards.acm.org/homepage.cfm?srt=all&awd=140.

[5] By an institution, I mean a structured organization with a particular purpose.

[6] Upon the suggestion of Dr. Sonnert and with approval of Dr. Fox, the third question was left for post-dissertation research: *Recognition*: How do the post-award career outcomes (participation, position, productivity, recognition, mobility) compare with the pre-award outcomes?

1) *Award-Winning Contributions*: What are the valued characteristics of award-winning contributions to computing and the method of selection of these contributions used by the Turing Committee deciding on the award?

2) *Education and Careers of Winners*: Which factors (educational and career-related, including collaboration) are associated with the winners of the Turing Award and differentiate them from the control group of non-winning computer scientists?

Knowing what constitutes a valued technical[7] contribution in a new field, how scholars get recognized, and what educational and career paths they take is particularly important in the field of computing. Because of the recent and interdisciplinary origins of computer science, multiple standards of performance operate and impact careers of computer scientists (National Research Council [NRC], 1994; Patterson, Snyder, & Ullman, 1999; Pollack & Snir, 2008). Knowledge gained in this study helps to clarify the criteria used in judging prize-winning contributions in computing, and the merit-based compared to non-merit based distribution of Turing Awards, with implications for broader participation and performance in the recently emerged field of computer science.

As a discipline concerned with "the construction, programming, operation, and use of computers,"[8] computer science had and still has a variety of names (e.g., informatics, computing, information/communication technology/science). However, both computing and computer science are commonly used in computing literature, particularly in the *Communications of the ACM*.[9] Since computer science has established itself as a legitimate academic discipline (see chapter 2), throughout this dissertation, I refer to it as a science. When I use the term "computing," I refer to computer science and industry broadly since science constitutes only part of computing (see chapter 2).

The Focus on Computing

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[7] I use the term "technical" interchangeably with "scientific." By "scientific/technical" I mean the contributions to the body of knowledge ("science") in computing regardless of their nature (e.g., mathematics, engineering, psychology). See chapter 2.

[8] Computer science. (n.d.). In *Oxford English Dictionary Online*. Oxford University Press. Retrieved September, 2011 from http://www.oed.com/view/Entry/270171.

[9] The *Communications of the ACM* magazine is "the most trusted and knowledgeable source of industry information for today's computing professional." See http://cacm.acm.org/about-communications.

Computing is a strategic research site[10] for the study of recognition through prize-winning. Being relatively new, and combing several disciplinary traditions, computing has multiple and competing standards of performance and lower consensus (than established disciplinary fields) in judging the significance of contributions, with consequences for recognition. Interdisciplinary research, which grows rapidly in the life, physical, engineering, and computational sciences, will soon change disciplinary taxonomies of the National Science Foundation (Klein, 2010). The growth of interdisciplinary research demands attention from sociologists to the understanding of successful careers in these fields. In interdisciplinary fields, the scholarly community is not well formed, which can reduce opportunities for recognition (Pfirman & Martin, 2010). In addition, ambiguous evaluation criteria, likely to be found in interdisciplinary departments and settings, can create conditions for the operation of particularistic biases (Long & Fox, 1995) that may disadvantage and hinder the careers of scientists whose contributions do not match the "preferences" of a given group of evaluators. The questions explored in this study—the kind of contributions that receive awards and how peers evaluate contributions in a new field and decide on a winner—affect both scientists working in the field and those aspiring to enter it. Many scientists begin with aspirations for achieving greatness and making their mark in the science by believing in the illusion of heroic individual performance (Hermanowicz, 1998). However, they soon realize that the reality in science is that "greatness is almost never achieved" and "most people aren't prizewinners, period" (Hermanowicz, 1998, p. 209).[11] Knowing what defines excellence becomes important for scientists of all levels who seek to contribute to computer science and to be recognized.

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[10] Strategic research site refers to strategic reasons for choosing the object of study (research site) that allow "getting to the heart of a problem" (Merton, 1973, p. 60). Merton (1988) also used the term "strategic research material" (SRM) for the same concept. At the methodological level, Merton introduced the concept of the strategic research site, meaning that a research design exhibits to advantage, and in an accessible form, the phenomena to be explained or interpreted. See Merton (1961/1973) and Fox, M. F. (2004). R. K. Merton—Life Time of Influence. *Scientometrics*, 60(1), 48.

[11] A study by Jonathan and Stephen Cole (1973) reported that the physicists holding most prestigious honors also held other high prestige awards while 72 percent of the national sample of physicists had received no awards at all (p. 48).

SIGNIFICANCE OF THE STUDY

Understanding the valued characteristics of contributions, the method for selection of winning contributions, and the educational and career paths leading to recognition in the field of computing are important for the following reasons: 1) awards such as the Turing Award bring visibility to selected scientists and their contributions, whose success and excellence may attract new talent; 2) winning contributions promote standards for judgments of other contributions in this field, and as a result, the clarity of the method of professional evaluation and selection for the Turing Award is likely to promote knowledge production in the field, while the lack of clarity may impede[12] it; and 3) understanding organizational affiliations (e.g., work places and professional societies) and their contributions to the recognition, that is, to winning the Turing Award, can provide guidance for such organizations on ways to support the contributions and the recognition of their affiliated scientists. By addressing the questions about the valued characteristics of contributions, the method of selection, and the roles of education and distinctive careers among award winners, one may learn about elements associated with success among these highly recognized scientists, and the ways that scientific communities and organizations might foster the development of a diverse scientific workforce.

Recognition in Awards

Awards are an important part of the reward system of science, because they communicate excellence and success. Awards recognize individual scientists by conferring symbolic esteem (and increasingly large financial rewards) for their contributions (Zuckerman, 1977), thus validating a given scientist's role performance. They also bring visibility to the work of awarded scientists and to the organization granting the award (Cole & Cole, 1973). Honored scientists become "statesmen and diplomats of science" (Cole & Cole, 1973, p. 52).

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[12] Lack of clarify is likely to have (negative) consequences, however, evidence is unclear if lack of clarity in fact impedes "knowledge production."

Attracting talent to scientific fields, specifically to computer science, is part of the agenda of industry, government, and academic organizations (Cohoon & Aspray, 2006; Klawe, Whitney, & Simard, 2009; Varma & Frehill, 2010). By the year 2018, the demand for computer scientists is expected to grow by 24%, software developers by 21%, and computer systems analysts by 20%, all faster than the average for all occupations (Bureau of Labor Statistics, 2010). Computing and computers are changing many spheres of human activities, including digitizing, automating, and creating intelligent "thinking machines" that interface with people and other devices. Such projects are likely to inspire current and future generations of students to pursue careers in computer science and engineering. Career preferences of students are known to be a function of their self-identification with a field (Cotgrove & Box, 1970, p. 81; Feist, 2006) and their perception and evaluation of job conditions in a field (Fox & Stephan, 2001). Because individuals will seek those positions "which they expect to be most rewarding" (Cotgrove & Box, 1970, p. 79) and most congruent with their perceived performance and talent (Feist, 2006), this study of the careers of Turing Award scientists helps to both illuminate the paths to recognition and reward, and in turn, potentially open research careers in computing to broader and more diverse groups of participants.

Determinants of Professional Recognition

Recognition is social, as other scientists play an important role in supporting, nominating, and selecting winners. Knowing "how" they go about doing this and what they value is important for understanding how the field operates. Being a relatively new field, computer science (and computing in general) offers rewarding opportunities for professional participation (Abbate, 2010; Hermanowicz, 2009). However, these rewarding opportunities are being missed by some people and groups who lack the means to the achievement (Davis et al., 1996; Stewart, Malley, & LaVaque-Manty, 2007). Sociologists have long demonstrated that although the institution of science is marked by "intense commitment to achievement over ascription," it exhibits "the same structures of discrimination as other occupations" (Zuckerman, 1988, p. 530). A study of highly successful scientists, that is winners of the Turing Award, will examine achievements of successful scientists and determine how the computing community recognizes its members. Knowledge of what distinguishes winners from non-winners of the Turing Award will contribute to understanding how patterns of inequality (i.e., stratification) in recognition arise in computing, and what accounts for differential recognition.

Scientific recognition in the form of awards is important because awards reify and exemplify excellence (Husu & Koskinen, 2010) and set a standard for the judgment of all contributions (Fox, 1983, 1985). Since computing is critical to the functioning of a technological society, it is important to encourage achievement in this field by promoting excellence and meritocratic distribution of rewards. In particular, having clear standards of excellence can help to promote clear criteria for the assessment of other contributions (Long & Fox, 1995). Applying universalistic principles in evaluations for awards—those based on impersonal criteria and previously confirmed knowledge, and not on "personal or social attributes of protagonist" (Merton, 1973, p. 270), can help to further the institutional goal of science of extending certified knowledge, that is, advancing computer science.

Organizational Affiliations

Scientific work takes place in organizations that "may either facilitate or inhibit performance" (Fox & Mohapatra, 2007, p. 542) or recognition (Frey, 2006), which in turn affects scientific careers. The way scientists transition through educational institutions, work organizations, and related professional social structures may also provide differential access to opportunities (based on access to information, and human and material resources) and thus shape the distribution of career opportunities and outcomes in scientific fields. However, past research in occupational sociology (and to an extent in sociology of science) has largely neglected the critical areas of: 1) "the multiple, interrelated dimensions of career attainment that organizations can influence," 2) "the diverse career strategies" employed by individuals or groups, and 3) the interactions of individual characteristics and those of jobs and organizational structures (Barnett, Baron & Stuart, 2000, p. 89). Additionally, little is known about recognition and careers in computing in two major sectors where most computer scientists work, academia and industry (Barker, Cohoon, & Sanders, 2010). Although the scope of this study cannot fully address all the differences arising from employment in different sectors and the full impact that organizations have on careers (it is not an area of contribution of this study), it seeks to assess broadly those aspects of workplaces directly related to recognition: that is, the choice of work sector (or organizations) and level of prestige of institutions where winners worked at the time of recognition. Information on the choice of sector and prestige of the employing institution may suggest grounds for further explorations.

CONTEXT OF THE STUDY

Stratification, Inequality and Success in Science

Stratification of scientists into status groups is a pervasive process that defines American science (Cole & Cole, 1973). Scientists can be stratified by a number of factors such as the prestige level of their education, level of income, the prestige of the institution and/or position held, socioeconomic origin, age, administrative authority or intelligence (Blau, 1977). The top strata of any population have been named the "elite." Functionally defined, "elite" refers to "the top status of any status dimension" (Blau, 1977, p. 47). Two of the most prominent differences (defining status dimensions) among scientists are observed in 1) publication productivity (Allison & Stewart, 1974; Cole & Cole, 1973; Fox, 1983; Fox & Mohapatra, 2007; Long, 1992; Long, Allison, & McGinnis, 1993; Lotka, 1926; Price, 1963; Prpic, 1996) and 2) awards (Cole & Cole, 1973; Prpic, 1996). Because scientists are usually evaluated on the basis of publication performance, scientific productivity creates the most explicit dimension for inequality. Those who have the highest measures of productivity (high number of total publications and/or the number of citations) fall within the top strata of the distribution of productivity and have a stronger case for recognition. Similarly, awards also communicate status, enhance reputations and further stratify the scientific community in respect to recognition already achieved.

Since the Nobel Prize Foundation does not recognize achievements in computing, the Association for Computing Machinery promotes the Turing Award as equivalent to the Nobel Prize in computing (Gotlieb & Horning, 2010; Lynch & Herzog, 1995).[13] Arguably, it is the most famous award in computing. [14] Compared to other ACM and non-ACM computer awards, the Turing Award is unique in its visibility, substantial prize money ($250,000), and the standard of excellence that it attained within the diverse community of computer professionals (see Appendix A on the origin of the Turing Award). The Turing Award signifies one of the highest technical honors within the interdisciplinary (in origin) field of computing, quite easily *ne plus ultra*,[15] making the recipients of the award the top status group in the computer field, or simply the *elite* among the computer professionals. In computing, as in other fields, a small group of scientists possess most of the prestigious honors and awards. The following statistics list the distribution of honors, which form a stratified pyramid of recognition in the U.S. among computer professionals who, until recently, were trained as engineers, physicists, and mathematicians:[16]

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[13] I did not find where this claim originates (from news reporters or from ACM administrators). However, the ACM administration clearly embraced the claim as indicated by the given references.

[14] The Turing Award is not the only award in computer science but it is the most central award in the field. One of the earliest awards in the area of computing was the 1964 American Federation of Information Processing Societies (AFIPS) Harry Goode Award, recognizing achievements in the information processing fields and named after an American computer and systems engineer. A few years later, in 1966, the Association for Computing Machinery (ACM) instituted the Turing Award (for technical contributions) while its big sister organization, the Institute of Electrical and Electronics Engineers (IEEE) Computer Society, instituted the W. Wallace McDowell Award (for a range of innovative contributions).[14] Later in 1969, the Data Processing Management Association (DPMA) instituted the Computer Sciences Man-of-the-Year Award (later renamed the Distinguished Information Sciences Award in 1980). Not all organizations persisted through the years; however, two major societies in computing in the United States—IEEE and ACM—survived and maintained their dominance. Together they annually bestow close to 44 awards (IEEE-CS [26] and the ACM [17] in 2011), which is still a small number compared to the thousands of computer professionals. Among these awards, the ACM A. M. Turing Award is the most prestigious and positions itself as the Nobel Prize in computing (Lynch & Herzog, 1995). Some Turing Award winners also have been awarded a Kyoto Prize by Inamori Foundation. The Kyoto Prize is an international award presented annually since 1985 in each of the three categories: Advanced Technology, Basic Sciences, and Arts and Philosophy. Each category is comprised of four fields. For example, the Advanced Technology category contains Electronics, Biotechnology and Medical Technology; Material Science and Engineering; and Information Science. As we can see, the Kyoto Prize is not given exclusively for achievements in computer science. There are only six Kyoto Prize winners in the Information Science and they all are Turing Award winners.

[15] "No more beyond" (Latin).

[16] For a stratification pyramid of the American scientific community, see Zuckerman, 1977, p. 9. To the best of my knowledge, no stratification pyramid exists of publications and citations in computer science. However, such a pyramid is within the capabilities of the Web of Knowledge.

131,876 scientists have been profiled in the biographical directory *American Men and Women of Science* (26th ed.) in 2009.

21,231 doctorate degrees were awarded in computer science from 1966 to 2006. These data came from the National Science Foundation/Division of Science Resources Statistics (NSF/SRS); the Department of Education/National Center for Education Statistics: Integrated Postsecondary Education Data System Completions Survey; and the NSF/SRS: Survey of Earned Doctorates.

24,642 scientists were listed in the "Engineering" section of *American Men and Women of Science* (26th ed.) in 2009.

17,958 scientists were listed in the "Physics and Astronomy" section of *American Men and Women of Science* (26th ed.) in 2009.

11,527 scientists were listed in the "Mathematics" section of *American Men and Women of Science* (26th ed.) in 2009.

5,517 scientists were listed in the "Computer Science" section of *American Men and Women of Science* (26th ed.) in 2009; this number showed a small (difference=542) increase from 4,975 in the 17th edition of the directory published in 1989-1990.

243 members of the National Academy of Engineering were elected to its Computer Science section prior and including 2010.

57 Turing Award winners honored by the Association for Computing Machinery from 1966-2010.

39 members of the National Academy of Science were elected to its "Computer and Information Sciences" section from 1970-2010. Among these members were 19 Turing Award winners and only one matched scientist.

The processes of peer evaluation have been found to contribute to stratification in performance and to location in the prestige hierarchy of science (Cole & Cole, 1973; Zuckerman, 1977). Since such stratification is not always obvious, what constitutes the elite is contentious and "harbors a fundamental ambiguity" that could lead to various doctrines of biological and social elitism (Zuckerman, 1977, p. 6). As a result, in the study of scientific winners, and thus of elites, it is important to address factors and processes contributing to the formation of elites, as I do below.

THEORETICAL PERSPECTIVES

The topic of social stratification has occupied sociologists of many generations as reflected in the classical as well as contemporary sociological theories. Building upon the contemporary sociological theories, the present study maintains the commitment to middle range theories that address delimited aspects of social phenomena and combine theoretical concepts with empirical research (see Merton, 1945, 1949/1957).[17] For the purposes of this study, I review research on status attainment, specifically models of attainment and reward in academic science. Status attainment models commonly emphasize stratification as the process through which individuals attain positions based on their characteristics and resources (Goldman & Tickamyer, 1984).

In the matter of classic perspectives on social inequality, Davis and Moore (1945) in their functionalist theory of stratification attempted to explain the distribution of prestige and the allocation of positions. Their theory explained the difference in the rank of positions based on a) individual functional importance to society and b) requirements of training or talent. According to their theory, the status and material rewards of certain positions are reflected in the skills and social responsibility pursued by those willing to undergo the required training. The authors argued that the legitimacy of functional elites was implicitly supported by equitable, merit-based access to these positions. In another classic perspective, Tumin (1953) demonstrated the inadequacy of the functionalist theory, arguing that social stratification, supported by social inequality, distributes to different groups an unequally favorable self-image[18] that may be necessary for the development of creative potential, a "sense of significant membership in the population," loyalty, and motivation to participate in certain activities (p. 393). Further, Tumin argued that society provides limited possibilities for discovery of talent due to individuals' unequal access to "appropriate motivation, channels of recruitment and centers of

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[17] In his 1945 article "Sociological Theory" Merton describes a way of integrating theory and empirical research but he did not use the term "middle range" theory which he later developed in his book "Social Theory and Social Structure," published in 1949. Talcott Parsons embraced Merton's suggestions, seeing the merit of the focus on "middle theory level," see for example, Parsons, T. (1950). The Prospects of Sociological Theory. *American Sociological Review, 15*(1), 3-16.

[18] Research in psychology revealed the importance of influence of self-image and personality on scientific interest. Self-image consists of self-perceived ability. The congruency between talent, performance, self-perception and drive were found to be the best predictors of career interest (Feist, 2006). Similarly, cognitive traits of openness and conscientiousness (desire for order, and organization), social traits of dominance, assertiveness, and loneliness, and motivational traits of achievement and ambition describe scientists as a group (Feist, 2006). Further, "the more creative scientists are more confident, open, dominant, independent, and introverted than their less creative peers, who are higher on these dimensions that nonscientists (Feist, 2006, p. 121). Traits and abilities correlate with achievements but they alone do not explain career outcomes such as contribution and recognition.

training" (p. 393). Thus, he maintained that institutionalized social stratification, based on social inequality with a seemingly positive function of matching the most qualified persons with the most important positions, also undermines the development of talent of the underprivileged and limits their access to important contributions and rewarding positions in society.

In the next few decades, researchers conducted a number of influential studies of occupational success. Blau and Duncan (1967) developed a status attainment model based on ascribed characteristics (one's socioeconomic status, father's education and occupation), achieved characteristics (child's education), and a few career factors (i.e., first job). They found that although individual success was affected by social background, "educational achievement played a greater role" (Bottero, 2005, p.76). Their finding established the importance of achieved characteristics while acknowledging the importance of ascribed characteristics, for example, that a child's opportunity for education is affected by family income and cultural knowledge. The educational system converts linguistic and cultural competence ("cultural capital") transmitted by families into credentials that become further means of social mobility (Bourdieu & Passeron, 1970/1990). Sewell and his colleagues improved Blau and Duncan's model into what became known as the "Wisconsin model" of status attainment by adding social psychological variables (Sewell, Haller, & Portes, 1969; Sewell & Hauser, 1975). With the growing popularity of network analysis, social scientists questioned the role of networks in status attainment. Nan Lin, Walter Ensel, and John Vaughn (1981) examined the impact of social resources (contacts with high status individuals) in one's networks on status attainment and found evidence for that. Social networks constitute an individual's social capital through which he/she can access or mobilize various resources and rewards such as jobs, information, trust and possibly recognition (Lin, 1999). The importance of social networks has been codified in *social capital* and *network theories* (Burt, 1992; Coleman, 1988, 1990; Granovetter, 1973, 1985; Lin, 1999, 2001; Lin, Ensel, & Vaughn, 1981; Lin, Vaughn, & Ensel, 1981).

Since the present study focuses on scientists and scientific achievements, findings and theories pertaining to stratification and recognition in science and the processes leading to the formation of scientific elites are particularly pertinent to this research. Several studies have examined and described elite scientists as a group. In comparison to non-elite scientists, elite scientists (identified by performance) tend to hold positions within select institutions and engage in intensive and extensive communication and collaboration with other elite scientists (e.g., Nobel laureates; Mulkay, 1976; Zuckerman, 1967). They are oriented toward theoretical rather than applied research (Amick 1973, 1974). They subscribe to more journals (Shaw, 1956), occupy positions of authority (e.g., the heads of large research labs), and often judge contributions and allocate research funds (Mulkay, 1976). Elite scientists are highly selective in their choice of a mentor (and mentee), and attend a few select educational institutions (Zuckerman, 1967). In fact, convergent patterns in the attended universities were found by Cao's (1999) study of social origins and education of elite Chinese scientists (based on membership in the Chinese Academy of Sciences) as well. In regards to publications, elite scientists are highly productive and tend to "avoid becoming either team man or lone wolf" and thus oscillate between the two (Zuckerman, 1967).

The understanding of successful outcomes in science involves identifying success and multiple factors contributing to those outcomes. This task is not easy because success in science has different markers and intermediate measures. In a number of published studies, authors have measured success in both broad and narrow terms: winning a prestigious postdoctoral fellowship and persisting in science (Sonnert & Holton, 1995a), winning a fellowship competition (Guetzkow, Lamont, & Mallard, 2004), and winning a Nobel Prize (Zuckerman, 1977). Across a number of studies, two variables measuring publication productivity have been most central in assessing success in scientific careers: they are 1) the number/rate of publications and 2) the number of citations associated with perceived quality of work, impact and visibility (that is, "to be easily seen") in the scientific community (Cole & Cole, 1968, 1973; Long, 1978; Long, Allison, & McGinnis, 1979; Long & McGinnis, 1981; Long, Allison, & McGinnis, 1993).

Other related career studies examined the impact on scientific careers of factors such as scientists' research specialization (Leahey, Keith, & Crockett, 2010), the prestige and rank of the graduates' current affiliation and previous doctorate programs (Keith, Layne, Babchuk, & Johnson, 2002), honorific awards and prestigious fellowships, gender, and academic rank (Cole, 1979; Long, 1978; Long, Allison, & McGinnis, 1979; Sonnert & Holton, 1995b). A study of scientists by Sonnert and Holton (1995a) identified the following elements contributing to career success, particularly for men: 1) choice of institutions (high-caliber institutions emphasize achievement and science); 2) choice of research topics and fields; 3) a strong publication record of research results; 4) a good mentor; 5) knowledge of the rules of political departmental games; 6) investment in networking; and 7) ability to work hard ("to transfer intellectual excitement into long hours of routine work and attention to detail") (pp. 173-175).

The formation of the scientific elite is strongly associated with social processes accounting for the distribution of rewards. The outcome of winning, that is, of being recognized, exhibits the same duality found in other social phenomena: it is a product of external/structural factors (e.g., broadly defined as scientific community, social processes/structures, rules of selection) as well as of individual actions (e.g., individual performance).[19] The distribution of rewards can be organized to emphasize either side of this duality as demonstrated by two different mechanisms of advancement (mobility) operating in social systems: contest and sponsored[20] mobility (Turner, 1960/1966). Whereas contest mobility is similar to a sporting game where prizes go to the best performers (and an individual may have more control over the outcome), sponsored mobility is early selection and "sponsored induction into the elite" of those who have appropriate qualities (Turner, 1960/1966, p. 451).

In explaining success and inequality leading to formation of elites in science, sociologists of science have developed a number of theories that can apply in explaining

[19] The differences between "structure" and "agency" have been explored by classical social theorists such as Marx, Durkheim, and Parsons (see Bottero, 2005, p. 54). A contemporary social theorist, Anthony Giddens, in his theory of structuration argued for duality of structure and agency, in the sense that structure was not external to human action but was reproduced by human agents across time and space with the help of rules and resources (traditional structural elements) (Giddens, 1984).

[20] Sponsored mobility occurs in a system when "elite recruits are chosen by the established elite or their agents, and elite status is given on the basis of some criterion of supposed merit and cannot be taken by any amount of effort or strategy." Contest mobility occurs in "a system in which elite status is the prize in an open contest and is taken by the aspirants' own efforts" (Turner, 1960/1966, p. 450).

success in computer science. The *structural functionalism* approach in the sociology of science, known for its macro-level view and scientific methods of analysis, is represented by the work of Robert Merton and Harriet Zuckerman, who emphasize the normative structure of science. One of the four norms describing the operation of science, the norm of universalism, for example, finds its expression in the imperative that scientists and their contributions are evaluated according to their performance and based on "pre-established impersonal criteria: consonant with observation and with previously confirmed knowledge" in order to advance scientific knowledge (Merton, 1942/1973, p. 270). Zuckerman and Merton distilled a number of theories to explain stratification and success in science, among which is the *Matthew Effect,* a tendency for more eminent scientists to receive greater credit and rewards than their less eminent colleagues, and the principle of *cumulative advantage,* accounting for amplification of small differences throughout scientific careers (Merton, 1968/1973; Zuckerman, 1977). According to Zuckerman (1977), advantage can accumulate by addition—receiving a certain ascribed advantage at some early point in time, and later resources "irrespective of their occupational role performance," or by multiplication—being judged "on functionally relevant criteria" as being most effective in making use of resources and thus being given resources (p. 60). This chain of events results in having more resources to perform and greater achievements, thus producing "elites of achievement" (Zuckerman, 1977, pp. 60-61).

An attempt to construct a model of the scientific reward system has been undertaken by Cole and Cole (1973) in their study of stratification system of American science. Their model included the measures of I.Q., rank of doctoral department, quantity and quality of publications, rank of current department and visibility to colleagues (score). Their model can be improved upon by incorporating variables related to scientific social capital. *Social capital* and *network theories* (Burt, 1992; Coleman, 1988, 1990; Granovetter, 1973, 1985; Lin, 1999, 2002; Lin, Ensel, & Vaughn, 1981; Lin, Vaughn, & Ensel, 1981) suggest that one's networks can be instrumental in rewards received; however, little is known about the kinds of individuals who can facilitate rewards and recognition. The most visible and measurable professional network that a scientist has is of his/her collaborators. The collaborators could be instrumental in submitting nominations, writing letters of recommendation or evaluating candidates whom they know. The contribution of collaborators to the process of determining winners of the Turing Award deserves further investigation.

Finally, scientist's visibility in the research community can influence the chances of recognition (Cole & Cole, 1973). Since the Turing Award is bestowed by a scientific organization, being known by key decision-makers, in particular by the ACM community of scientists, has consequence for being considered for their most elite award. Professional associations and study societies are committed to promoting their fields and building their own legitimacy and, as a result, become instrumental in formalizing elite professional status of some of its members (Abbott, 1988; Larson, 1977; Wilensky, 1964). In this way, proximity and visibility in an organization and professional networks and/or collaborations become a prerequisite of professional success.

An insightful perspective on the relationship between successful careers in science and academic institutions was introduced by Hermanowicz (1998; 2009), who argued that academic scientists' definition of success is shaped by their work environment. In his longitudinal study of scientists and the effect that institutions have on their academic careers, he documented changes in the beliefs and the behaviors of scientists in elite, pluralist, and communitarian worlds over the course of their careers. These academic worlds correspond to three prototypes with distinct characteristics. The elite academic world exemplifies private and public institutions that place a premium on research; pluralist institutions place a premium on research and teaching; and communitarian institutions on teaching "in the presence of research" (Hermanowicz, 2009). He observed that over the course of their careers professional aspirations of mid-career scientists in elite institutions intensify, in pluralist institutions diminish, and in communitarian institutions either subside or dissipate. As a result, scientists experience different levels of orientation to work, aspirations, productivity, recognition, and satisfaction, depending on their academic worlds. Thus, success in science can be understood partly in relation to the employing institutions in which scientists are located. For this study of recognition, I will incorporate two institutional variables: the institutions where scientists got their first jobs and the institutions where they were located at the time of receiving the Turing Award.

Studies of recognition in the areas of sociology of culture and sports are disparate and bear little applicability to this project; however, since the scientific society also has a culture (Goldin & Gingras, 2000) they raise a similar question regarding the operation of recognition in the scientific culture. The studies in sociology of culture and sport interpret achievement and recognition as cultural valorization and social consecration taking place in a range of areas (e.g., among writers, actors, scientists and athletes). A study by Boltanski & Thévenot (1991), for example, examined recognition in the form of fame and associated with it justifications of worth.[21] Other studies explored cultural markets of prestige. By studying prizes in arts and literature, James English (2005) made a number of observations about American culture, specifically that while the public is ambivalent and uncertain about prizes, various industries and organizations use prizes to produce "value."[22] In the field of entertainment, a study of the Grammy Awards explored the functions of award ceremonies in attracting attention to the field and legitimizing some of its members (Anand & Watson, 2004). Another study of Academy Award nominations examined the relation between artistic achievement and collaborative networks (Rossman, Esparza, & Bonacich, 2010). The celebrity culture became so pervasive that a number of sociologists claimed that celebrity became an important form of contemporary status hierarchy (Kurzman et al., 2007). The world of sports is no exception to celebrity culture. A study by Allen and Parsons (2006) of the Baseball Hall of Fame proposed a theory of cumulative recognition in sports where the likelihood of consecration is affected by the "cumulative effects of social characteristics and circumstances, prior social recognition, and media discourse, as well as by objective differences in achievement" (Allen & Parsons, 2006, p. 808). Achievement in sports is primarily based on performance that is "measured." Likewise, the normative structure of science, in its classic formulation (Merton, 1942/1973), also postulated that rewards are based on performance. A continuing question has been: to what extent is this the case?

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[21] It also alluded to the existence of a theory of honor where the most worthy beings are "those to whom the greatest number of others attribute signs of honor" (Boltanski & Thevenot, 1991/2006, pp. 99-100).
[22] English (2005) used the term "the economy of prestige" that includes sectors of economy where prestige plays a critical role (e.g. entertainment industry, art).

Studies of highly recognized scientists (Cao, 1999; Cole & Cole, 1973; Feist, 1997; Zuckerman, 1977) are critical to the understanding of inequality in science because they identify the factors associated with strong success. By studying elite scientists, we can gain a more comprehensive understanding of how elites are made and how the reward system operates, given that it is structured so that it allows only a limited number of scientists to attain such status. The careers of Turing Award winners are marked by a distinguished technical award, signifying their professional success and elite status. However, gathering data only on the elite group of Turing Award scientists would not explain how they are different from, or similar to, other computer scientists. The control group of non-Turing Award winners who were trained in the same institution, with the same advisor during a comparable time period, makes it possible to identify factors associated with strong success of winning, *compared with* not winning, controlling for the institution, status of the department, and eminence of the advisor.

HYPOTHESES

Question 1: Award-Winning Contributions

The first question: *What are the valued characteristics of award-winning contributions to computing and the method of selection of these contributions used by the Turing Committee deciding on the award?*

I intend to examine the characteristics of contributions that are valued and recognized by the Turing Award Committee and the methods for their selection using qualitative research methods and data on award citations and committee decision-making found in archival documents. This approach allows for a more complete description of contributions, and informs the study about the value system, and the criteria and the process used by the committee in deciding on the winner.

I find it reasonable to assume that Turing Award winners are recognized for work that is regarded as "original" and "theoretical" (that is, more basic science as opposed to applied—the criteria that were observed to distinguish the work of other elite scientists, see Amick 1973, 1974; Zuckerman, 1977). However, I neither propose a hypothesis about the first question nor intend to test it because of the ambiguity surrounding the contributions for which the awards were granted. Contributions were not clearly specified in the award citations, and as a result, I make a point to investigate what was awarded and why. Using qualitative research methods, I identify up to three contributions stated in the award citations and analyze their characteristics. These analyses, together with the criteria used for judgment of contributions inferred from the archival documents related to the Turing Award Committee, will help clarify *what constitutes an award-winning contribution*. I intend to examine recognized contributions over time because the preferences and values of award committee members may have varied over time, from year to year (for example, in respect to recognized research area: theoretical/mathematical vs. empirical, engineering).

Question 2: Education and Careers of Winners

The second question: *Which factors (educational and career-related, including collaboration) are associated with the winners of the Turing Award and differentiate them from the control group of non-winning computer scientists?*

Although this study has two central questions, I am posing hypotheses associated only with the second question. These hypotheses reflect career attainments that were likely to be positively associated with the nomination and evaluation of candidates for the award. I consider factors that were likely to influence scientific careers from graduate (i.e., Ph.D.) education to employment prior to the year of the Turing Award. I address only some aspects of education, namely, the career advantages associated with having a graduate fellowship, publication with an advisor, and a first job at the top five programs for computer science. I do not include other educational differences because I control for educational origins and advisors: Turing and the control group scientists come from the same schools and were trained by the same advisor during a comparable time period.

I aim at assessing hypotheses about becoming a successful and recognized scientist as informed by theoretical positions, and not to test, directly, theories accounting for stratification in science. Given a relative dearth of theories on the subject of recognition ("bestowing a prize"), this study is designed to *assess the best available factors associated with success in science that positively contribute to recognition in computer science*. Therefore, to examine the second question—which factors are associated with Turing Award winners (career outcome of "becoming eminent") and distinguish Turing Award winners from non-winning scientists—I propose the following hypotheses:

<u>a. Publication Productivity</u>

The norm of universalism in science maintains that rewards should be given for scientific contributions (Long & Fox, 1995; Merton, 1973; Parsons, 1951) that are "most clearly indicated by measures of research productivity" (Long & Fox, 1995, p. 60). Indeed, the publication productivity, measured by the rate of publications, was found to be the best predictor of how peers judge fellow scientists (Cole & Cole, 1973; Sonnert, 1995c), and I will use it to predict recognition with the Turing Award.

H1: Superior productivity: I expect the publication productivity (publication rate measured by the number of articles divided by years since graduation) of Turing Award scientists to be higher than that of the control group of scientists prior to conferral of the award.

<u>b. Impact</u>

The contributions of award winners were likely to have some outstanding characteristics such as creativity, quality or usefulness to make an impact on the community of researchers. Creativity contributing to quality of work is not apparent on its own but depends "on the effect it is able to produce in others who are exposed to it" (Csikszentmihalyi & Wolfe, 2000, p. 82). Quality of scientific work is found to strongly contribute to eminence (Cole & Cole, 1973) and is often measured by citations to publications. Although there may be a number of reasons why scientists would cite their colleagues' work (Hargens, 2000), citations also reflect the usefulness of research which some argue to be the preferred indicator of a scientific contribution (Long, 1992). A contribution worthy of the Turing Award must have had some outstanding characteristics to make a substantial impact on the community, reflected in the number of citations of a publication describing that particular finding or invention. I intend to use citations as a measure of the impact of the contribution that represents a clear evidence of outstanding qualities associated with the recognition.

H2: Impact of contributions: I expect the contributions of Turing Award winners, compared to non-winners, to have more impact and use to others, measured by the number of citations to a most-cited publication (article) prior to the Turing Award.

c. Number and Type of Collaborators

In addition to bringing intellectual capital, collaborators bring to scientists social capital through which they can access other resources (powerful networks, information, jobs, collaborative opportunities, consulting [see Burt, 1992; Coleman, 1988; Granovetter, 1973; Lin, 2001]). Social capital, embodied in relationships among researchers, generally takes on one of three forms: 1) "obligations and expectation, which depend on trustworthiness of the social environment, 2) information-flow capability of the social structures, and 3) norms accompanied by sanctions" (Coleman, 1988, p. S119). Thus, some benefits of having collaborators include access to collaborators' social status (former Turing Award winners) and networks (a collaborator could be helping to nominate or select a Turing Award winner). In the scientific community, as in other communities, moral bonds of trust not only facilitate knowledge transfer but also may be used in evaluation of peers in the decisions concerning rewards. Collaborators are well positioned to evaluate or recommend their colleagues because they are most knowledgeable about the significance of shared research and are likely to have similar values, outlook on research frontiers, and interest in promoting their research area.

Having a number of collaborators may not only increase the visibility of a researcher but also increase his/her access to the expertise of colleagues. As with other professionals, former collaborators are likely to respond with reciprocity in referrals and technical assistance (Osnowitz, 2006). It may also be the case that award-winning computer scientists in their networks were positioned at the intersections (also called structural holes) of social worlds/structures/disciplines—an advantageous position where they were more likely to be compensated for their creative ideas and appreciated for their performance (Burt, 2004).[23]

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[23] Between-group brokers are "more likely to have [their] ideas evaluated as valuable" (Burt, 2004, p. 349). Considering that computer scientists came from different disciplines, they represented "between-group brokers" bridging the discipline in which they were trained and a new computer field.

Since it is not known which collaborators are most "useful" for receiving awards, this study will assess three aspects of collaboration: a) number of collaborators which presumably positively relates to the chances of being nominated for an award; b) the presence of collaborators who already received a Turing Award, as they will most likely be asked to write recommendation letters; and c) the presence of former collaborators with prior experience of serving on a Turing Committee whose sponsorship could have contributed to receiving a Turing Award. All three types of collaborators can be said to represent "reputational entrepreneurs"—the parties with the "motivation, narrative facility, and institutional placement" (Fine, 1996, p. 1162) to create a reputation (image) for a candidate—who may have played an important part in justification of the award-worthiness in nomination and selection processes.

H3a. The number of collaborators: Compared to non-winners, Turing Award winners are likely to have a larger number of collaborators, a form of social capital (Coleman, 1988, 1990; Granovetter, 1973, 1985; Burt, 1992; Lin, 1999, 2001; Lin, Ensel, & Vaughn, 1981; Lin, Vaughn, & Ensel, 1981).

H3b. The type of collaborators: The collaborators (social capital) of Turing Award scientists, compared to non-winners, are likely to be compositionally different—have more distinguished coauthors such as Turing Award winners or members of the Turing Award Committee.

d. Early Career Advantages

Early career advantages may predict recognition in a way that these advantages increase scientists' chances of professional success. Through the process of cumulative advantage (Merton, 1973; Zuckerman, 1977), these advantages may set some scientists on successful career paths leading to publications and awards.

In the early stages of scientific careers, Turing Award winners and the control group share many similarities in their educational environment. Similar to Nobel laureates (Zuckerman, 1977), eminent computer scientists are likely to receive their training at a few select institutions with eminent advisors/mentors. The training in these departments shapes the norms, values, behaviors, research quality and problem choices of young scientists (Fox, 2003; Zuckerman, 1977). However, at this early stage of their scientific career, when scientists have not yet demonstrated their productivity, particularistic advantages are likely to take place (Zuckerman, 1988, p. 530). At the early stages, advantages may appear in the form of graduate fellowships, publications with advisors, and a first job in a prestigious department. Inequality among scientists will get greater as groups mature in professional age (this finding has been consistent over the years [see Allison & Stewart, 1974; Long, 1978, 1992; Zuckerman, 1977]). Early career advantages may prove to be a critical career factor that sets only some scientist on a path to contribution and recognition.

H4. Early career advantages (Zuckerman, 1988, p. 530): I expect Turing Award scientists, unlike the control group, to have begun their careers with small advantages such as a fellowship, a publication with their advisors (during or immediately after completion of the Ph.D.) or a first job in the top five programs in computer science.

e. Recognition/Eminence

Prior recognition and peer esteem, together with past successes, are likely to increase the probability of additional recognition (Merton, 1973, 1988). As discussed earlier, the tendency to award already famous researchers has been explained by both the pattern of cumulative advantages –"the social processes through which various kinds of opportunities for scientific inquiry as well as the subsequent symbolic and material rewards for the results of that inquiry tend to accumulate for individual practitioners of science" (Merton, 1988, p. 606); and by the Matthew Effect –"accruing of greater increments of recognition for particular scientific contributions to scientists of considerate repute and the withholding of such recognition from scientists who have not yet made their mark" (Merton, 1968/1973, p. 446). The achieved eminence represents a good predictor of additional awards, such the Turing Award. Recall Zuckerman's observation, "a Noble Prize rarely goes to unknowns" (1977, p. 199). On the part of the awarding organization, giving the award to scientists who have already achieved eminence for established contributions and who are renowned in the scientific community may constitute a (reasonable) calculated choice.

H5. Eminence and resulting visibility through prior awards: I expect Turing Award winners, compared to non-winners, to have received a substantially higher number of honors and awards than the control group prior to winning the Turing Award (and an equivalent number of years for the control group).

f. Institutional Location

Research has long established that being at a major university positively affects the likelihood of being recognized (Cole & Cole, 1973; Crane, 1965; Long, 1978). Crane's (1965) study of scientists at major and minor universities found a high correlation between the prestige of an academic setting (e.g., a university) and scientific recognition. To explain why scientists at major universities are more recognized, her study suggested that: 1) scientists at major universities may have a (more distinguished) record of achievement; 2) a "scientist's position at a major university places a 'halo' over his work so that it may look better to his colleagues than it actually is"; and 3) "recognition depends on visibility to colleagues outside a scientists' own university, and visibility can be enhanced either by productivity or by contacts with eminent colleagues" (Crane, 1965, p. 713). While all three conditions may be operating at once, being employed at a major university (i.e., being in the top five computer science programs) is a factor that links individuals and organizations and their combined chances of being perceived as award-worthy and that will be included in the analyses.

H6. Location in elite organization: At the time of attaining the award, the Turing Award winners, compared to non-winners, are more likely to have been employed in top universities.

<u>g. Visibility in ACM</u>

Membership in scholarly associations denotes access to a specific professional community of researchers and organized efforts to promote contributions to the field. Professional associations and study societies, by promoting their discipline, recognize and bestow awards on individuals and thus become an official means of professional status attainment (Abbott, 1988; Larson, 1977; Wilensky, 1964). With regard to the Turing Award, visibility in the ACM community would increase the chances of being nominated and selected for the Turing Award. As such, it is reasonable to assume that computer scientists who do not publish in ACM journals possibly belong to different societies and as a result are less likely to be noticed and considered for the Turing Award since "peer recognition can be widely accorded only when the correctly attributed work is widely known in the pertinent scientific community" (Merton, 1988, p. 621).

H7: Visibility in ACM: Compared to non-winners, Turing Award winners are more likely to be visible to the awarding organization (ACM) than the control group by having received an ACM award, published in ACM journals, or *served in ACM.*

To summarize, this study employs a range of theories[24] found to contribute to recognition: 1) Functionalism/universalism (*H1*: Publication productivity and *H2*: Impact/citation); 2) cumulative advantage and Matthew effect (*H4*: Early career advantage, *H5*: Prior eminence and visibility through prior awards, and *H6*: Location in elite organizations); 3) social capital (*H3a*: Number of collaborators and *H3b*: Types of collaborators); and 4) the logic of professions (*H7*: Visibility in ACM). Admittedly, some of these hypotheses and corresponding variables could support more than one theory—that is citations/impact could reflect the genuine merits of a contribution, or they could be a result of social capital, visibility or some other advantage. This concern applies to many variables in social science and requires more care in constructing

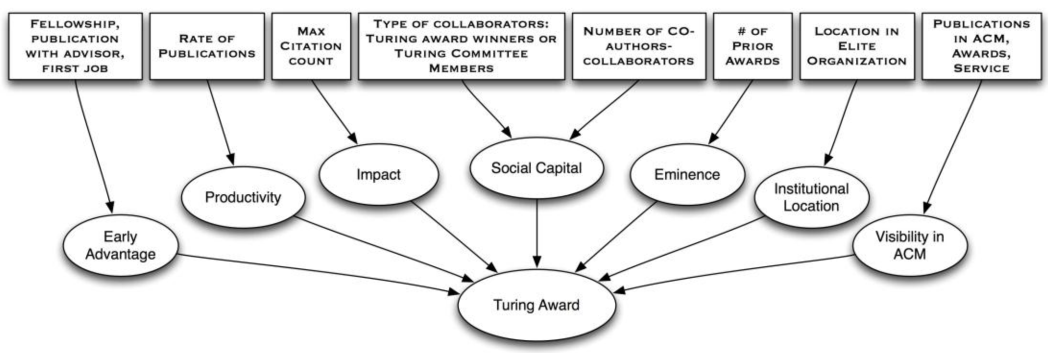

Figure 1.1. Representation of Factors Associated with the Receipt of the Turing Award

questions, measurements and interpretation of results.[25] Figure 1 summarizes the sets of variables affecting receipt of the Turing Award.

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[24] Considering that a wide range of descriptions can be called a "theory," Mullins & Mullins (1973) observed that theory usually contains "(1) abstract generalizations that move beyond simple descriptions of a particular incident or case and (2) an attempt to explain either why or how something happened on the basis of acceptable general principles" (p. 3).

[25] Confounding variables can complicate the interpretation of regression coefficients and drawing causal inferences from statistical analyses. To address these concerns I have taken the following measures: 1) variables were carefully constructed to reduce the overlap with each other to the extent it was possible, 2)

CORRESPONDING MODELS

I assess the hypotheses for the second research question using multiple logistic regression models. Based on the attributes of the group of winners and the group of non-winners, the logistic regression estimates the likelihood of being recognized with the Turing Award. I intend to test all of the hypotheses in tandem and to assess the strength of each variable in predicting the winners of the Turing Award. However, I would also like to investigate the effect of specific factors such as collaborators and reputational visibility associated with the awards and the location in an elite institution. To do so, I enter independent variables in a series of steps to highlight the contribution of the variables of interest in the presence (or absence) of other variables.

Toward understanding of recognition that applies to Turing winners, I constructed five recognition models that assess the importance of specific factors. *Model 1*, representing the "basic model" of recognition, considers only publications and citations—the measures that scientists use to evaluate each other and their scientific contributions. In *Model 2*, I add three *collaborative variables* to the basic model and identify the best variable associated with award winners among these three collaborative variables. In *Model 3*, I add an early advantage score and visibility in the ACM to assess all the variables in the absence of reputational information (e.g., awards, institutional location). The last two models introduce reputational measures: *Model 4* adds awards and *Model 5* enters location in an elite institution (see Chapter 3).

METHODS AND ORGANIZATION OF CHAPTERS

The methods are discussed in detail in chapter 3 and here I will only briefly summarize them. To answer two main questions that this study raises, I employ a mixed-method approach that combines quantitative and qualitative methods of analysis. I use qualitative research techniques—a thematic coding of award citations and an analysis of

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alternative explanations were considered and included into the models (Frank, 2000); 3) independent variables were ordered according to their "causal priority" and analyzed in a series of steps (Cohen, Cohen, West, & Aiken, 2003). Further, the relationship between the independent and dependent variables was defined as associational and not as causal.

archival documents related to the Turing Award Committee—to examine the valued characteristics of contributions. Using quantitative techniques, I use descriptive statistics to describe and compare the two groups of scientists (awardees and non-awardees) and then use multiple logistic regression to test the seven hypotheses outlined above. All hypotheses positively contribute to explaining recognition and are tested in tandem in a series of steps to assess the unique effect of *collaborators*, *awards*, and *institutional location* on recognition in relation to other factors. The dependent variable is "winning a Turing Award." The independent variables are the *early career advantage* score, the rate of *publications*, the maximum *citation count*, the best collaborative variable (*number of collaborators, coauthors already Turing Award-winners* and *coauthors who are members of the Turing Committee*), the number of prior honorific *awards*, employment in *elite organization*, and *visibility to the ACM*.

This study is organized into seven chapters. In chapter 1, I introduced the research topic, questions, and hypotheses and their relationship to the outcome of receiving a Turing Award and models for assessing these. In chapter 2, I review the history, formation, and nature of the interdisciplinary (in origin) field of computing to understand the disciplinary and professional identity of the new field. Chapter 3 contains all of the methods used in this study. Chapter 4 addresses findings on the characteristics of the recognized contributions of Turing Award scientists by examining the range and types of contributions recognized by the award and how the winners are selected—the criteria and evaluation processes used by the Turing Award Committee. Chapter 5 focuses on educational backgrounds and examines the educational patterns associated with Turing Award winners and the control group of scientists. This chapter also provides statistics on the countries of affiliation of Turing Award scientists, their academic degrees and institutions, fields of study, fellowships, and advisors; and compares the productivity of advisors with those of their Turing Award students. Chapter 6 examines the career attainments of Turing Award scientists prior to the receipt of the prize (compared to the control group) and assesses the hypotheses specified in the Introduction. Finally, chapter 7 summarizes the key findings of the study and provides additional implications and concluding remarks.

CHAPTER 2

THE FORMATION, HISTORY, AND NATURE OF THE FIELD OF COMPUTING[26]

This chapter provides background for the study by examining the origin, the formation, and the defining characteristics of the field of computing. Compared to other established fields such as physics, mathematics, and even engineering, computer science is newer, less coherent and less structured, which creates issues for the selection, training, and employment of professionals entering this field, and most likely for determining the merits of their contributions. I aim to provide a short overview of the history and rapid formation of computing in the second half of the 20th century in order to clarify the evolving identity of the field, particularly for readers without computing backgrounds. While examining the formation of the field, I review the growth of institutions and scientific organizations in the computer science. Specifically, I discuss focal activities of the Association for Computing Machinery (ACM) that helped to define the new discipline. The formation of the discipline included the establishment of university departments, degrees, and links to employing organizations—developments that had a bearing upon the understanding of educational and career paths of Turing Award scientists (the second question of this project). I examine how Turing Award scientists define the intrinsic characteristics (the nature of their discipline) because this helps us understand the valued characteristics of contributions (the first question of this project), specifically, what is "technical"—what is science and technology in computing? Thus, this chapter aims to inform the two central questions of this study about the professional structures, early training opportunities and workplaces for computer professionals, and the defining characteristics of the new discipline.

HISTORY

[26] For early history of computing, specifically the relationship between electrification and computation from 1880s to 1960s, see the dissertation by Aristotelis Tympas (2001), a Georgia Tech graduate. It is a pure happenstance that this study, covering the period of 1960s-2000s, picks up where he left off.

Development of Computers in the 20th Century

The development of computing in the 20th century has been influenced by historical events—the First and Second World Wars and powerful institutions of the government, the military, academia, and industry. During World War I, the tasks of calculation of the trajectories of weapons became more demanding, leading to the establishment of ballistic research programs that used scientific knowledge and demanded faster calculating machinery. Advances in science and technology (radar, jet aircrafts, rocketry, war chemistry, penicillin, the atomic bomb) figured prominently in the outcome of World War II. World War II dramatically changed "what it means to do science and radically altered the relationship between science and government…the military…and industry" (Zacharias qtd. in Forman, 1987, p. 152). During World War II, science was transformed into "Big Science,"[27] characterized by large-scale projects and large budgets, staffs, machines, and laboratories. Big Science was done not only in the nation's federal and industrial science labs of Los Alamos, Oak Ridge, Lawrence Livermore, Lockheed, General Electric, and MITRE but also in its universities. It was getting harder "to tell whether the Massachusetts Institute of Technology [was] a university with many government research laboratories appended to it or a cluster of government research laboratories with a very good educational institution attached to it" (Weinberg qtd. in Leslie, 1993, p. 14). The Radio Research Laboratory at Harvard employed about 600 people while the Radiation Laboratory at the Massachusetts Institute of Technology (MIT), the largest of its kind, employed about 4,000 people (Edwards, 1996, p. 47). In postwar years, the U.S. maintained its leadership in science, assured by its head start in technology, the availability of financial resources, capabilities in engineering and manufacturing, and ready access to the basic sciences in Europe (Krige, 2006). However, the resources of wartime research were redirected to new projects such as postwar computer development, initiating a new era of sponsorship of academic research (Akera, 2007).

[27] The term "Big Science" has been attributed to Alvin Weinberg (1961), director of Oak Ridge National Laboratory, who used the term in an article in *Science* magazine, and to Derek de Solla Price (1963), who used it in his book *Little Science, Big Science.*

Not all scientists welcomed military sponsorship, but the transition to sponsored research had already begun prior to World War II. Academic physicists, who had traditionally resented political and military control, preferred funding from private foundations. However, in the early 1930s, in the midst of the Great Depression, financial support for colleges and universities began to dwindle, for the resources of private foundations had been stretched, industrial sponsors were cautious, private institutional endowment was stagnating, and total financial receipts were sagging (Owens, 1990). Between 1929 and 1937, research universities such as Massachusetts Institute of Technology, California Institute of Technology, and New York University received substantially more modest gifts than schools such as Yale, Chicago, and Harvard (Owens, 1990). Coming to the rescue, federally sponsored research ensured the survival of academic institutions and had become an integral part of many research institutions, bringing a new order of academic learning.

The end of World War II brought about changes to universities that grew increasingly dependent on sponsored research. While some of the changes dealt with demobilization of projects (such as the Radiation Laboratory at MIT), the postwar relationship between the government and science remained largely uncertain. Acting in his capacity as a science advisor, in 1945, Vannevar Bush outlined the postwar "contract" between the government and science in his famous report *Science: The Endless Frontier*. The report encouraged the government to continue to invest in science and called for the formation of the semi-independent, civilian-controlled National Research Foundation. The news of the launch of Sputnik, the first Russian robotic satellite to be placed into orbit in 1957, came almost as a blessing to some, for it fostered political urgency, prompting the expansion of the federal sponsorship of science in the United States. In the 1950s, Vannevar Bush's suggestion attracted more attention, leading to the establishment of the National Science Foundation (NSF) and other government agencies sponsoring research. As a result, U.S. federal funds were committed to research and development (R&D) projects directed towards the continuation of the partnership between the military and civilian scientists for the sake of national security (Forman, 1987).

From the 1940s through the 1960s, the U.S. military remained "the single most important driver of digital computer development" (Edwards, 1996, p. 43). Academic research in computing was conducted in academic departments, special laboratories with a strong academic base (e.g., MIT's Lincoln Laboratory, a Research Laboratory for Electronics), and computational centers (Akera, 2007), all funded by military research organizations (such as the Office of Naval Research, Communication Security Group, Air Comptroller's Office, see Edwards [1996]). By the early 1950s, academic physicists and hundreds of educational institutions were completely or partially funded by the Atomic Energy Commission (AEC) (Forman, 1987) or the Department of Defense, that sponsored the Jet Propulsion Laboratory at the California Institute of Technology and the Applied Physics Laboratory of the Johns Hopkins University. With the help of military funding, the MIT staff doubled, the budget quadrupled, and the research budget grew ten-fold, "85% from the military services and their nuclear weaponeer, the AEC" (Forman, 1987, p. 157). In the wake of the Korean War (1950-1953), the NSF budget was still being negotiated as the military needs and sponsorships of existing projects were perceived to be more urgent by Congress as well as by the beneficiaries of funds.[28] One of the opponents of changes in government sponsorship was President DuBridge of the California Institute of Technology, who argued that if funds were transferred to the NSF, his school would "go broke" (Kevles, 1990, p. 259).

Emerging after World War II as the largest nonindustrial defense contractor, MIT maintained this position throughout the Cold War (Leslie, 1993), while other universities were eager to get involved. Stanford, at the time a second-rank regional university, was among the first to take advantage of available government support for academic research, deeming it a "wonderful opportunity" that would make it a top school in science and engineering (Lowen, 1992). Building on their strengths in the strategic disciplines of electronics, aeronautics, material science, and physics, both MIT and Stanford greatly prospered financially and intellectually from military contracts and were subsequently

[28] See "The National Science Foundation: A Brief History." (1994, July 15). Retrieved September 2011 from http://www.nsf.gov/about/history/nsf50/nsf8816.jsp

followed by other universities such as the University of California at Berkeley, the University of Michigan, California Institute of Technology, and later Georgia Institute of Technology and Carnegie Mellon University (Leslie, 1993). However, military patronage, directing the advances of the sciences, had another side that conflicted with academic values. Military contracts constrained the flow of knowledge (resulting from the need for secrecy of classified information) and influenced the character of academic knowledge, that is, a push for applied research, creating the weapon-driven "world of the mind" (Foreman, 1987).

Between 1935 and 1945, a handful of prominent universities received an early start in computing through military grants that sponsored the development of "one-of-a-kind" digital computing machines (Campbell-Kelly & Aspray, 2004, p. 59). One of the early electromechanical computers was the Mark I (also called the Automatic Sequence Controlled Calculator [ASCC]), designed by Howard Aiken from Harvard and built by IBM between 1937 and 1943. It was sponsored by the U.S. Navy and shipped to Harvard in 1944. Between 1943 and 1946, the University of Pennsylvania's Moore School of Electrical Engineering worked on the ENIAC (Electronic Numerical Integrator and Computer) for the U.S. Army under the leadership of John Mauchly and J. Presper Eckert. Other schools attracted their own sponsors. The Statistics Laboratory at Columbia University benefited from a generous donation of IBM computers by Thomas Watson, Sr. of IBM. The U.S. Navy contracted the MIT Servomechanisms Laboratory to create a computer for a flight simulator, project Whirlwind. This project proved to be important for the areas of business computing and minicomputers in the 1960s. By the early 1960s, computing "came of age" as evidenced by adopted hardware architecture (based on transistors) and a pattern of commercial computing in industry and computer centers in universities established for the next few decades (Ceruzzi, 2003).

During the early years of computing (the 1940s), about ten machines were constructed by various organizations: government agencies, industrial research laboratories (AT&T, RCA), technical departments of office-machine companies such as Remington, NCR (National Cash Register Company), IBM, and universities. Reflecting on these developments, Michael Mahoney, a prominent historian of computing observed that the history of computing can be traced not to one, but to many computers and various "communities of practitioners" who adopted computers for their unique use in data processing, management, production, maintenance, and mathematical calculation of businesses, industry, government, military and academia (Mahoney, 2005/2008). All in all, it came as no surprise that the computerization of society was, in fact, a side effect of the computerization of war (Rose, 1984).

FORMATION OF COMPUTER SCIENCE

Institutionalization and Professionalization of Computer Science

Computing machines were widely used in business and the military in 1940s-1960s. However, because these machines were novel, the work associated with early computers was performed by employees with a range of educational backgrounds in mathematics, physics, and engineering. A new profession,[29] concerned with the application of knowledge in the context of computers, was yet to emerge. Compared with older professions (medicine, law, engineering), the new area of computing lacked a "clearly established cognitive structure" and people were free to take on available tasks in the emerging field (Abbott, 1988, p. 83). As a result, "the very lack of an identity as 'the computer profession' or of programmers as anything more than people with a fairly limited but necessary skill has proved a distinct advantage" (Abbott, 1988, p. 84). Thus, the rise of the computing profession has been "a story of knowledge in triumphant practice" (Abbott, 1988, p. 1).

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[29] In 1957, when one Turing Award winner got married, the Justice of the Peace did not accept the designation of "programmer" as a profession for the records because no such occupation had been identified. Occupations are often used to describe the tasks that a worker performs, and thus occupations have become the mechanism of dividing and managing labor (Abbott, 1988; Damarin, 2006). A "profession" can be defined as an occupational group possessing a special skill that is usually abstract and requires training (Abbott, 1988). Not all occupations are professions but these two words are commonly used interchangeably. "Profession" is commonly associated with expert knowledge and independent judgment. A profession has evolved to mean an occupation in which one "professes knowledge of some branch of learning" (Hughes, 1994, p. 38). Using Hughes' expression, professionals "profess to know better than others the nature of certain matters and to know better than their clients what aids them or their affairs" (Hughes, 1994, p. 38).

The formation of any new profession and a corresponding academic field entails a competitive struggle among the proponents of the existing and the new disciplinary and institutional structures (Bourdieu, 1999; Larson, 1977; Strauss, 1975). While industry and military embraced and helped to train computer professionals, the institutionalization of computer science in academia was not smooth, and it often involved struggle. How can a field whose identity is vague and whose claims of being a science are inherently questionable take its place among more established disciplines and become a science? One fact remains certain: the demand for computing was strong and the new discipline was aided by growing public interest and desire for training, a steady supply of jobs, and corporate and military funding which nurtured education and research in the new field of computing.

The formation of the discipline of computer science was contingent on a number of critical developments such as the creation of scientific social structures, the demand for trained professionals in industry, the institutionalization of the discipline in universities, and the development of intellectual and professional identity. To organize the sequence of these events, I will use a framework developed by social scientists, Nicholas and Carolyn Mullins (1973) and Gregory Feist (2006), about the formations of fields. This framework does not intend to provide extensive coverage of all key events (e.g. meetings, publications, new departments) that led to formation of the field, but only a broad overview. Feist's (2006) three-stage model[30] of the development of scientific disciplines, adopted from Mullins and Mullins (1973), distinguishes three stages in the formation of a discipline: *isolation*, *identification,* and *institutionalization.* I introduce

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[30] In his book *The Psychology of Science and the Origins of the Scientific Mind*, Gregory Feist (2006) simplified Nicholas and Carolyn Mullins' (1973) framework and adopted it for outlining the developments of the sociology and the psychology of science. Mullins' book *Theories and Theory Groups in Contemporary American Sociology* explored how theories are developed, why some are similar and others are different, and why some theories die out. He described a general model for the development of sociological theories consisting of four stages: normal, network, cluster, and specialty or discipline. During the normal stage, founding father(s) outline the theory; in the network stage, informal relations dominate and theory attracts other scientists, training centers are organized and collaborations are formed; during the cluster stage, more publications are written, meeting and jobs are available but success leads to divergence; and finally during the specialty stage, activities continue and research is diffused.

this framework to show that these three stages were very recent and that the Association for Computing Machinery (ACM) and its activities (including the Turing Award) were an important part of the institutionalization process as they helped to solidify the intellectual identity of computer professionals.

During the *isolation* stage of computing in the 1930s and the 1940s, scientists and engineers working in specific contexts produced original works that led to the creation of computing machines. In 1937, British mathematician Alan Turing, in his influential paper "On Computable Numbers, with an application to the *Entscheidungsproblem*," brilliantly connected configurations of a virtual computing machine which could be physically built to human computing. The analogy with "thinking" was achieved by breaking complex operations into smaller steps/states performed consecutively and recording the states on a tape (acting as memory). As a result, Turing machines, with the ability to follow ordered operations in solving problems, could be thought of as capable of "thinking." The invention of a representation of a computer as a Turing machine provided a solid theoretical foundation for the yet nascent discipline.[31]

The discipline of computer science was in the beginning stages during the early 1940s with the development of critical theories in algorithms and mathematical logic and the invention of the stored-program electronic computer (Denning et al., 1989). A fundamental question dominated many research agendas in computing: What could be (efficiently) automated (Denning et al., 1989)? Early computers were mechanical calculating machines until the invention of the universal computer (usable for different tasks), which had two unique features:

(a) ability to store and execute programs that carry out conditional branching (i.e., programs controlled by their own results to an arbitrary level of complexity)

(b) ability to manipulate any kind of symbolic information, including numbers, characters, and images. (Edwards, 1996, p. 27-28)

[31] See the acknowledgement of Turing's contribution by the ACM, "Perlis Invited as A. M. Turing Lecturer for 1966; First Time ACM Honor is Bestowed." (1966). *Communications of the ACM, 9*(1), 47.

Professional Organizations

During the second stage, *identification*, people began to identify with the field of computing and a new professional identity was born. In the period between 1946 and 1947, post-World War II computer advances stimulated a need for sharing knowledge about the capabilities and the operation of newly built computing machines, prompting various organizations to organize professional meetings. In January of 1947, the Harvard Computational Lab hosted a large meeting, the third largest conference in the field of new computing machinery, titled "The Symposium on Large Scale Digital Calculating Machinery," attracting over 300 participants (Berkeley, 1947, January). The previous six meetings on digital and analog computing machinery, hosted by the American Institute of Electrical Engineers (AIEE) at Columbia University, New York, had attracted about 200 people, indicating a high level of interest in new computing machinery. In addition, in March and April of 1947, the Department of Electrical Engineering at MIT held meetings on electronic computing machinery attended by over 100 people, also demonstrating increased interest in the subject of computing machinery.

Although engineering associations (e.g., American Institute of Electrical Engineers [AIEE] and the Institute of Radio Engineers [IRE]) had been actively hosting discussions on computers, it remains a puzzle as to why the need for a new association in computing, the ACM, arose. The answer may lie with the sheer volume of researchers interested in computing or perhaps the dearth of information on the subject of computers. The idea of the new association came from the MIT professor of Electrical Engineering, Samuel Caldwell (during a symposium on January 10, 1947), and historians speculate that his proposition stemmed from a disdain for the secrecy associated with military-sponsored computing projects. "Given the youthful status of the field," Akera commented, "[Caldwell] was especially concerned that academics retain a commitment to openness" (Akera, 2006, p. 32). The need for a new organization was embraced by a group of conference attendees who assumed the role of a temporary committee hailing from a variety of organizations: insurance companies, military manufacturing, the Bureau of Standards, the Office of Naval Research, universities, and engineering companies. Each member represented an organization of power and financial backing.

From the 64 organizations whose representatives expressed an interest in taking part in the association, about 33 represented commercial and private firms, 14 represented universities, and the remaining 17 represented governmental or military agencies/offices (ACM, 1947, August 21). This diversity of organizations indicated that research in computing was taking place in a range of sectors, but in many cases, with some ties to the military.

At that time, support for the new association (ACM) was not always strong. A letter from John von Neumann to Edmund C. Berkeley, while stating his interest in the work and the development of such an organization, opined that “such an association is a highly desirable one ultimately but that the general situation has not yet matured sufficiently to make the present moment the optimum one to found it” (von Neumann, 1948). Similarly, Howard Aiken thought that “there’s no need, really” (Akera, 2006, p. 41). Reflecting on the development of the discipline, Edsger Dijkstra, a prominent computer scientist and Turing Award winner, admitted that the establishment of the computer science in the United States had taken place too prematurely, when the foundation for the discipline has not yet been developed. Not surprisingly, since earlier departments of computer science in the U.S. predated the science of computing, “they were no more than ill-considered cocktails of presumably computer-related topics that happened to be available on campus” (Dijkstra, 1986, EWD952). Europe at that time had no resources to spare for the construction of machines, so the subject found its home in departments of mathematics and became more theoretical (with a different title “computing science” or informatics) (see Dijkstra, 1977, EWD611).

Development of University Programs

During the *institutionalization* stage, various universities established programs in computer related areas and, with the appearance of training and degrees, professional identity of computer professionals became more defined. University education legitimized the credentials of trainees and infused their knowledge with the best scientific knowledge available at that time. However, in many cases, the development of computer science university training was a gradual process muddled by a precarious future and an uncertain identity of the new area of inquiry related to computers (Pollack, 1982).

During the second half of the 20th century, when computers first appeared on American campuses, they had two purposes: use in scientific research and use in educating students (Aspray & Williams, 1994). By the 1950s, computers were recognized as important tools in scientific research and by 1953, the newly-formed National Science Foundation (in 1950) "was receiving grant proposals with computing requirements" (Aspray & Williams, 1994, p. 60). Expenditures on computers in academia were growing rapidly—in the millions of dollars. If in 1957, 40 computers were present on U.S. campuses, in 1964, the number rose to 400 (investments of about $250 million), and the expenditures on computers were estimated to continue to grow, compelling the National Academy of Science to recommend more federal aid to cover computer costs (Carter, 1966).

Although many disciplines (physical, biological, management, social sciences) had computational needs, the computer facilities of research universities in the 1950s were relegated to a single general purpose: a computing laboratory or center, which served the needs of an entire campus.[32] As a result, many requests for such facilities were submitted to the Mathematical, Physical, and Engineering Sciences Division of the NSF, but NSF funding could not always be provided. The "single strongest impulse" in introducing computers to campuses came from IBM, which not only had state-of-the-art equipment but also offered a 60 percent discount to universities and even donated some of their first computers (Aspray & Williams, 1994). Other manufacturers (Burroughs, Sperry Rand, Bendix, and Royal McBee) also donated computers, but on a smaller scale. By 1959, 150 colleges and universities had some instructional or computer research initiatives. However, if computer science was to grow, universities would need to separate instruction and research operations from computing services (such as university business operations).

Computer instruction developed haphazardly on university campuses (Aspray & Williams, 1994; Pollack, 1982). For one, university departments often struggled to

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[32] Sharing a computer was not always easy. Computer center staff often complained about a waste of "precious" computer time by physicists and students running trivial problems.

recruit knowledgeable faculty, and when they did, the faculty often left shortly after they were recruited, pursuing opportunities in other institutions. In addition, the formation of computer science departments often involved internal institutional struggles among engineering and mathematics departments and university administrations. In some cases, professors refused to join units where computer science was in a dependent position to other disciplines.[33] It was not until the 1960s that the first independent units of computer science were formed and degrees conferred. However, because of increased interest in computers and the demand for computing education, universities started offering courses and seminars much earlier.

One of the earliest surveys of schools offering computer training, conducted by the IRE Professional Group on Electronic Computers in 1953, represented 121 out of 155 schools, only 90 of which reported having facilities or computer courses. Within those 90 schools, only a few universities (University of Arizona, University of California in Los Angeles [UCLA], Massachusetts Institute of Technology [MIT], University of Pennsylvania, Pennsylvania State University, Wayne State University, and University of Wisconsin) reported granting degrees in electronic computation (which was still part of engineering) (Goode, 1955). A number of universities were holding regular seminars in electronic engineering (Georgia Institute of Technology, University of Idaho, University of Illinois, Lafayette University, University of Michigan, Oregon State University, Princeton University, Texas A&M University, Purdue University, and Tulane University, not counting schools granting degrees listed above). Only a small number of universities had facilities and equipment for digital computation such as digital general-purpose (as opposed to analog/special purpose) computers (UCLA, Columbia University, Harvard University, University of Illinois, Kansas State University, University of Michigan, MIT, New York University, Purdue University, University of Tennessee, U.S. Navy Post Graduate University, and Wayne State University). By 1958, the number of universities

[33] Being under another discipline meant that another discipline sets the qualifying requirements (math intensive or engineering intensive) that may discourage and weed out non-mathematical students interested in computing, which occurred at Purdue (Rosen & Rice, 1994).

that had computers grew to 50 and by mid 1960s, the number grew to 90 (Finerman, 1969).

The ACM had an important influence on structuring computer education in universities by developing guidelines for college curricula. Its preliminary recommendations for curricula in computer science, published in 1965, already produced "a coherent definition" of the computer science major (Pollack, 1982, p. 35). Subsequently, in 1968, the ACM published *Curriculum '68*, a guideline for computer science programs that became "an important landmark for computer science education" (Pollack, 1982, p. 38). The curriculum established computer science as a separate discipline with a strong focus on algorithms and languages and solidified the mathematical nature of the computer discipline (which represented a search for "beauty and elegance" as opposed to a pragmatic orientation) (Pollack, 1982, pp. 35-41). As the use of information processing in education was becoming more pervasive, many colleges wanted to establish academic programs using the published curriculum. Because the needs of small or liberal arts colleges differed from those of technical universities, the curriculum had to be adjusted to fit the particular needs of various universities. The ACM Curriculum Committee "felt a responsibility to interpret [the curriculum] to the academic community" by providing consultation and later accreditation (ACM, 1971). In addition to helping to develop university curriculum, the ACM also produced various career guidance[34] and reference literature for students and played an important role in educating American society about computing. The ACM Education Committee established the Computer Sciences Theater Subcommittee (CST), which evaluated and disseminated information on movies and visual aids for computer science education.

The institutionalization of computer science on university campuses took various forms. For example, numerous programs that were quick to respond to the growing

[34] Career guides were also published by Data Processing Management Association ("Your Career in Data Processing"), by the National Council of Teachers of Mathematics (NCTM) in the 1960s ("Computer Oriented Mathematics – An Introduction for Teachers"), the National Science Teachers Association (NSTA) ("A List of Publications on Careers in Electronic Data Processing"), and in 1964 even by the U.S. Office of Education ("Electronic Data Processing in Engineering, Science, and Business").

interest in computing offered either an associate or bachelor's degree in business data (electronic) processing, management, and computer programming. A few schools offered advanced degrees, but the focus of those degrees varied: they were either science-based (mathematics or information science) or engineering-based. Aaron Finerman, computer science educator, noted that by 1964-1965 U.S. universities were offering over 200 degree programs in computer field but with different names, concluding with a facetious remark "obviously, we had given birth to a healthy and robust infant discipline, but could not decide on a proper name, or indeed the correct identity of the parents" (Finerman, 1969, p. 17). Table 2.1 displays the list of first schools reporting a computer science curriculum and offering a Ph.D. degree in computing (in 1967).

A few universities got an early start in computer education. The MIT, the University of Pennsylvania, Harvard University, Princeton University, and Columbia University were the first to install or develop computing facilities. These schools were successful in securing scarce government and industry funding for computer facilities, recruiting faculty, and offering computing services to the rest of the school. Aspray (2000) provided an interesting comparison of the development of computing in these schools. MIT highly profited from its strong ties to industry, the government, and the military. At MIT, computing to this day remains part of its electrical engineering department, one of the most important departments on campus; the department that strengthened research in computing. Computing at Harvard, on the other hand, started strong but was stifled by organizational issues. After its initial successful collaboration with IBM, which eventually went sour, the university relegated computer science to a sub-group within the Division of Engineering and Applied Physics, hindering its development. Harvard perceived computing as a fundamental (though applied) science, thus elevating it above a "useful but mundane real-world problem" typically pursued in engineering (Aspray, 2000, p. 57). Similar to Harvard, the University of Pennsylvania and its Moore School of Engineering got an early start because of the experience of John

Table 2.1. Universities offering a computer science Ph.D. curriculum in 1967[35]

University	Degree Program/ Department
American University	Technology of Management
Brown University	Applied Math
California Institute of Technology (Caltech)	Math, Engineering, Sciences
California, University (UCLA)	Math, Engineering, and Appropriate Depts.
California Institute of Technology (Pasadena)	Math, Engineering, Sciences
Carnegie Institute of Technology (CMU)	Systems and Communication Science
Case Institute of Technology	Computer Technology
Chicago, University of	Mathematical Methods and Computers
Cornell University	Dept. of Computer Science Engineering
California, University (UC Berkeley)	Computer Science Option in EE and Computer Science Dept in College of Letters and Sciences
Georgia Institute of Technology (Georgia Tech)[36]	Information Sciences and Applied Math
Harvard University	Applied Math
Illinois, University of	Math, Electrical Engineering, Physics
Iowa, University of	Computer Science
Iowa State University	Computer Science
Massachusetts Institute of Technology (MIT)*	Computer Science Option within EE Dept.
Michigan, University of	Communication Science
New York State University*	Computer Science
Pennsylvania, University of	Computer and Information Science in School of EE
Penn State University	Computer Science
Purdue University	Computer Science
Southern Illinois University	Information Processing Science
Stanford University	Computer Science
Texas, University of (at Austin)	Information Processing, Math (Num Anal)
Utah, University of	Computer Science (in College of Engineering)
Washington University (at Seattle)	Operation Research and Systems Analysis
Washington University (at St. Louis)	Operation Research and Systems Analysis
Wisconsin, University of (at Madison)	Computer Science
Yale University	Computer Theory

* These schools were not a part of the original document but were added based on other relevant information.

[35] The list was compiled based on the archival document; see "Colleges and Universities Reporting ‘Computer Science’ Curriculum," 1967, August 29.
[36] Georgia Tech received its first facilities, the Rich Electronic Computer Center, in December 1955 with a help of three different funding sources that also helped to acquire NCR-102-D digital computer by the National Cash Register Corporation and ERA-1101 by the Remington-Rand Corporation (McMath et al., 1985, p. 252).

Mauchly and Presper Eckert in electronic computing. However, the school later suffered from post-war civilian redeployment (losing key faculty) and the uneasiness of the administration about post-war military support (Aspray, 2000). Columbia also got an early start, thanks to IBM's generous donation of computers, resulting in establishment of the Watson Scientific Computing Laboratory. At first, the new lab provided instruction in applied mathematics and the scientific application of computing. When computing outgrew its laboratory space, Columbia's two departments of electrical engineering and mathematical statistics began to offer a computer science curriculum. Lastly, Princeton, with its long tradition in mathematical logic and physics, got an early start due to John von Newmann's early wartime experience with computers. However, computing found a home in its Department of Electrical Engineering, first as a program in computer science and later as computer engineering, leading to the renaming of the department in 1976 into Electrical Engineering and Computer Science (computer science became a separate department in 1985).[37]

It is interesting to note that the universities that first initiated programs in computer science (MIT, University of Pennsylvania, Harvard, Princeton, Columbia) did not gain a decisive advantage of early entry in such a way as "to continuously build itself into a leading department of computer science" (Aspray, 2000, p. 81). However, they did establish reputations and links with government and industry sponsors and gained marketing value from having early programs.

It may come as surprise that the first department of computing was established at Purdue University, a school that entered computing late. Even then, its entrance into the field, involved a share of conflict, and continuous troubles in recruiting new faculty. Prior to the establishment of the computer science department, a conflict arose when the Department of Mathematics, seeking independence from the School of Science, Education and Humanities, proposed the creation of a new Division of Mathematical

[37] The profiles of 40 best known universities in computer science are available in Tölle, W., Yasner, J., & Pieper, M. (1993). *Study and research guide in computer science.* New York: Springer-Verlag.

Sciences that would include computer science as opposed to making it independent (Rosen & Rice, 1994). The proposal went through and the first department of computing in the United States was established in Purdue in 1962. As the department matured in 1970s, new changes were taking place “from a mathematics-like discipline (using only paper and punched cards) to a science-like discipline with a significant experimental science component” (Rice & Rosen, 1994, p. 52). The math-based computing at Purdue was becoming more in-line with that at engineering schools. As the field grew, the status of computing rose and finally in the 1980s the National Science Foundation gave it an institutional status similar to that of other disciplines. As we have seen, computing first found its place in the departments of engineering and mathematics and later made its claims as an independent science.

Development of Scientific and Professional Associations in Computing

During the *institutionalization* stage, various organizations helped to disseminate information pertaining to new developments in computing and facilitated the formation of social structures through annual conferences and local chapters. By forming and joining societies of researchers with similar interests, those working with computers solidified their new professional identity. A profession “can only be said to exist when there are bonds between the practitioners, and these bonds can take one shape—that of formal association” (Carr-Saunders & Wilson, 1964, p. 298). The Eastern Association for Computing Machinery was proposed in June and formed during the first meeting on September 15, 1947 “to advance the science, design, construction, and application of the new machinery for computing, reasoning, and other handling of information” (ACM, 1947, June 25). The word “Eastern” was added to differentiate the association’s activities from computing activities on the West Coast, but the word was soon dropped from the name because the membership became nationwide. The word “Association” was a source of debate, with alternatives being “society,” “organization,” and “institute.” The founding subcommittee, responsible for choose a name and consisting of John Russell of Columbia, E. G. Andrews of Bell Telephone Laboratories, and Edmund C. Berkeley, settled on “association” because it “represented fraternalism in a way because there was kind of a small fraternity at that time, only a few hundred, and everybody knew each other" ("Twentieth Anniversary Conference of the Association for Computing Machinery," 1967, p. 72). In the next fifteen years (by 1962), the organization had grown rapidly to 25 times its original size (see Table 2.2).

Table 2.2. Growth of ACM membership, 1947-1961[38]

Selective Years	Members	% Increase in members between selective years	Rate of change per year (number of members)
1947	350		
1949	599	71	125
1951	1113	86	257
1952	1149	3	36
1953	1161	1	12
1954	1537	32	376
1956	2305	50	384
1959	5254	128	983
1961	8788	67	1767

However, so did the number of computer installations. In the 1950s and 1960s, the number of computer installations increased to almost 500 times its original number (Table 2.3).

Table 2.3. Growth of Computer Installations, 1950-1975[39]

Year	Number of Computers	% Increase in computers between selective years	Increase in the number of computers per year
1950	12.5		
1955	1000	7900	198
1960	6000	500	1000
1965	30800	413	4960
1970	60000	95	5840
1975	85000	42	5000

In 1971, the American Federation of Information Processing Societies (AFIPS) estimated that a total of 1 million people worked in computing; 440,000 of whom were keypunch

[38] The data was provided by Franz Alt, 1962.
[39] The data comes from AFIPS, (n.d.), "The State of the Information Processing Industry [1950s-1970s]."

operators (of whom 99% were women), 210,000 programmers, 200,000 computer operators, and 150,000 systems analysts (AFIPS, n.d., “The State of the Computer Industry in the United States, 1971-1976”). AFIPS was an umbrella organization for close to nineteen constituent societies that spawn in computing ("Brief History of AFIPS and Its Constituent Societies," 1986). [40] Among them the largest associations were the Data Processing Management Association (DPMA), the Association for Computing Machinery (ACM), and the Institute of Electrical and Electronics Engineers – Computer Group (IEEE-CG).

The newly-formed association, the Association for Computing Machinery (ACM), took the form of a study society. Study societies were a common type of organization in the new wave of associations whose members had “in common only the desire to promote the study of some field…” (Carr-Saunders & Wilson, 1964, p. 301).[41] Thus, the ACM was established as an “educational and scientific” but not “professional” organization. On a number of occasions, the ACM had been accused of professional neutrality as if the “professionals” were not concerned with the morality and social implications of computer work (“Computer Professionals for Peace,” 1969). While refusing to participate in political, social, and labor issues, the ACM was by no means “neutral,” as observed in its actions supporting the professionalization and ethics of computer professionals.[42]

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[40] Archival data provides information about the size and the overlap in memberships among societies (AFIPS, 1968). The ACM was the largest society and most diverse: it had members who were also par of the IEEE-CG (Computer Group), the Association for Computation Linguistics (ACL), the American Society for Information Science (ASIS), and the Simulation Council (SCI).

[41] Carr-Saunders and Wilson argued that study societies were not professional associations even though the members had more in common than just interest in a subject. In their study of professional associations existing in the early part of 19th century, the associations arising from study societies “first took upon themselves functions relating to the competence and honor of their members, and later included the protection of material interests and public activities while retaining study functions”—activities that the ACM attempted but did so neither wholeheartedly nor successfully (Carr-Saunders & Wilson, 1964, p. 303).

[42] This is an interesting area for future research. The ACM appeared to control professionalization “internally” but was reluctant to support “external” interests of computer professionals.

In 1980, a group of scientists went on to establish yet another new society, the American Association for Artificial Intelligence (AAAI), for the sub-field of computing that became the area of specialization of computer science departments at Stanford and Carnegie Mellon University. One of the IEEE members wrote to AAAI leaders, Edward Feigenbaum and Allen Newell (both Turing Award winners), asking "Why is it that professional associations such as the IEEE Computer Society (or even the ACM) do not provide a sufficiently broad haven for activities like those that may be intended through AAAI?" (Garcia, 1980, September 2). Allen Newell responded, saying that alternatives "might have transpired," artificial intelligence (AI) "never had a strong presence within the IEEE," and it fact, Feigenbaum and Newell were not really involved in the formation of the AAAI; and that it was the founding council (particularly Raj Reddy, Turing Award winner) that "went outside of itself" to select its presidents (Newell, 1980, September 9). In his presidential address, Allen Newell pointed out that scientific societies "are not for their members, they are for their science" (Newell, 1980, p.1). In several rambling paragraphs, he was unable to give a strong reason for why the AAAI was created and "why [it took] this form rather than some other one," nor did he feel that he needed to. Apparently, "the time was ripe," for enough people showed interest. One of the few real alternatives was the ACM, which he believed was "a very large professional-scientific society, somewhat bureaucratized, also weighted" (Newell, 1980, pp. 2-3). He thought that minimal and restricted societies better perform their functions and that a new society would be different: "We will be anti-bureaucratic; more concerned with getting things done than with procedure; more concerned with minimizing the effort required than with formalities. In a word, more concerned with the science than with the organization" (Newell, 1980, p. 4). Although it is difficult to imagine how one could have artificial intelligence without some kind of artifact (or computing machinery), the establishment of AAAI comes across as a separation of the science of AI from the technology of AI. The portrayal of the ACM as a semi-professional organization, however, was not unfounded.[43]

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[43] By 1973, the ACM Constitution listed an additional purpose: "to develop and maintain the integrity and

Defining the Purpose of the ACM and the Field of Computer Science

The ACM played an important role in the formation of the discipline (that this chapter describes) by facilitating the dissemination of information and helping to solidify professional identity of computer professionals. Multiple journals of the ACM became venues for publication of research results in computing.[44] The national conferences, special interest groups, and local chapters provided opportunities for interaction and exchange of information. As other academic associations,[45] the ACM developed means to recognize achievements of its members. High profile awards in computing, such as the Turing Award, were instrumental in attracting public attention, funding for research, and elevating status of the field. The stories of outstanding contributions helped to create a (heroic) *saga* in the culture of computing. With few computing awards and thousands of computer professionals, receiving such an award was an ultimate recognition for a researcher. Furthermore, by supporting all these activities—learning, awards, publications and meetings, ACM provided what professional organizations usually do—

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competence of individuals engaged in the practices of the sciences and arts of information processing" (ACM, 1973). Both additions are retained to this day, explicitly using the phrase of promoting "the highest professional and ethical standards" (see Table 2.3). However, these additions pose the question of how a non-professional association can promote and uphold its members to professional ethical standards? The contradiction resides in the fact that the ACM is not willing to call itself, explicitly, a professional association or to support the professional interests of its members. However, it does so by holding members accountable to professional and ethical standards and supporting their accreditation. By 2010, the purpose of the "non-professional" ACM had not become that much different from the original purposes of the professional engineering association, the IRE: "Its objects shall be scientific, literary, and educational. Its aims shall include the advancement of the theory and the practice of electronics, radio, allied branches of engineering, and related arts and sciences, their application to human needs, and the maintenance of high professional standards among its members. Among the means to this end shall be the holding of meetings for the reading and the discussion of professional papers and the publication of papers, discussions, communications, and such other matters as may be appropriate for the fulfillment of its objectives" (IRE, 1953).

[44] Originally there were only three journals but then the number of publications grew rapidly. The *Journal of the Association for Computing Machinery* (published quarterly since 1954) was dedicated to "research papers of lasting values," the journal *Communications of the ACM* (published monthly since 1958) was for "prompt up-to-date technical and professional information in all areas of computation"), while *Computing Reviews* (published bi-monthly since 1960) was "founded to monitor the world's information processing literature, in all languages, with comprehensive reviews" (ACM, 1964). A few years later (in 1969), *Computing Surveys* was established which published the results of survey and tutorial materials.

[45] The French Academy of Sciences established many important precedents in the development of modern science, one of which was the prize system (Crosland & Galvez, 1989).

"stimulation of the individual's work, recognition of his [her] contribution, and support of his [her] identification with the professional community" (Kornhauser, 1962, p. 86).

By refining its organizational purpose, the ACM was defining the field of computing. Whereas in the original statement of purpose of the ACM, the focus and perception of the field was centered around "construction" of new machinery for computing and handling of information, in the 1960s, the ACM redefined its purpose as advancement of "the sciences and arts of information processing" ("Brochure of ACM," 1961). By 2010 "information processing" was renamed into "information technology (ACM, 2010). The new (2010) conceptualization of the organizational purpose makes it clear that information technology (computing) is composed of art, science, engineering and applications (see Table 2.4). In all its attempts to define the purpose and the discipline, the evolution of the foci of the ACM demonstrates inclusiveness and desire to appeal to a broad range of members.

Table 2.4. Evolution of the foci of the ACM, 1947-2010

Year	The Purpose of the ACM
1947	The purpose of this organization is "to advance the science, development, construction, and application of the new machinery for computing, reasoning, and other handling of information" (ACM, 1947, June 25).
1948	The purpose of the Association is to advance the science, design, development, construction, and application of modern machinery for performing operations in mathematics, logic, statistics, and kindred fields, and to promote the free interchange of information about such machinery in the best scientific tradition ("Constitution and Bylaws of the Association for Computing Machinery," 1948).
1961	The purpose of this organization is "to advance the sciences and arts of information processing including, but not restricted to, the study, design, development, construction, and application of modern machinery computing techniques and appropriate languages for general information processing, for scientific computation, for the recognition, storage, retrieval, and processing of data of all kinds, and for the automatic control and simulation of processes" ("Brochure of ACM," 1961).
1973	The purposes of the Association are (1) To advance the sciences and arts of information processing including, but not restricted to, the study, design, development, construction, and application of modern machinery, computing techniques and appropriate languages for general information processing, for scientific computation, for the recognition, storage, retrieval, and processing of data of all kinds, and for the automatic control and simulation of processes.

Table 2.4 (continued).

	(2) To promote the free interchange of information about the sciences and arts of information processing among both among specialists and among the public in the best science and professional tradition. To develop and maintain the integrity and competence of individuals engaged in the practices of the sciences and the arts of information processing" (ACM, 1973).
2010	The purpose of this organization is to advance the art, science, engineering, and application of information technology, serving both professional and public interests by fostering the open interchange of information and by promoting the highest professional and ethical standards (ACM, 2010).

NATURE OF COMPUTING

Many disciplines contributed to the rise of computing, in particular, electrical engineering, physics, mathematics, and business/management. It is not surprising that for many years outsiders perceived computer science not as "a coherent intellectual discipline but rather heterogeneous collection of bits and pieces from other disciplines" (Forsythe, 1966, p. 839). Such perceptions called into question the legitimacy of advanced studies in computing, "Why should there be a special graduate (let along undergraduate) program in computer science any more than in electron microscopy, x-ray diffraction, or vapor phase chromatography?" (Forsythe, 1966, p. 838). George Forsythe, serving as ACM President (the only non-Turing Award winner mentioned in this section), thought that misconceptions about computer science primarily came from the "absence of reliable descriptive data concerning the scope of computer science, education, and industry" (Forsythe, 1966, p. 838). Forsythe, as other professionals in computing, thought that the core existed, as did "the way of thinking on the subject," but if unifying themes had not been made explicitly intelligible, misconceptions would persist.

For explanations and insights on the nature and the identity of their field, I turn to people who made significant technical contributions to the field of computing, recognized by the Turing Award. Reflections of Turing Award winners on the defining characteristics of their field were sometimes captured in the Turing Award lectures delivered during the award reception and in various other publications. Turing Award scientists held various views on the nature of their subject. While some (John McCarthy, Edsger Dijkstra) supported the notion that the subject had to be mathematical, others (C.A.R. Hoare, Marvin Minsky), although agreeing on its mathematical underpinnings, found such assessment problematic; yet others pointed out the non-mathematical aspects of the new science.

Computing as an Art and a Craft

A number of award winners (Knuth, Brooks, Hamming and Dijkstra) agreed that computing involves some aspects of craft and of art. Donald Knuth, in his well-known book *The Art of Computing Programming*, noted that the "process of preparing programs for a digital computer is especially attractive because it is not only can be economically and scientifically rewarding, it can also be an aesthetic experience much like composing poetry or music" (1968, v). Edsger Wybe Dijkstra, referring to programming methodology, stated that it was guided by aesthetic criteria such as simplicity, elegance, efficiency, and beauty, and as a result, programmers were also craftsmen "that to a certain extent had become artists as well" (1976, EWD566). When Niklaus Wirth recalled his experience of working on compilers that would automatically translate programs into machine code, he noted that one percent of it was science and 99 percent sorcery (Wirth, 1984/1987). Frederick Brooks (1982), in his book *The Mythical Man-Month*, referred to programming as a craft, explaining that it was fun because one often derives joy and pleasure from making things and especially from "making things that are useful to other people" (p. 7). A programmer experiences the "joy of always learning" and a fascination "of fashioning complex puzzle-like objects of interlocking moving parts and watching them work in subtle cycles" (Brooks, 1982, p. 7). Thus, programming was commonly perceived as both technical skill and art, and not only that.

Naur argued that programming (computing) was also theory building and "constructing models of aspects of the world from data processes" (Naur, 1990/1992, p. 49). He considered the process of creating descriptions (of physical and social world) an important part of doing science (Naur, 2007). Programming was theory building because the core of programming was the development of the understanding of matters. A similar insight was shared by Dijkstra, who (while disagreeing with Naur's research), argued that because computer programming is a human activity, it cannot be automated. He saw computing as a human activity in which computers have a valuable capability to "manipulate symbols and produce results of such manipulations" (1988, EWD1036). In his view, "computing science is—and will always be—concerned with the interplay between mechanized and human symbol manipulation, usually referred to as 'computing' and 'programming,' respectively" (1988, EWD1036).

Some scientists considered the art of computing to be a transition stage to science ("computing" to "computer science"). In 1967, Forsythe (not a Turing Award winner but a computer scientist and a president of the ACM who spent some time thinking about the field), in his provocative report "What to do till the computer scientist comes," argued that the computer science must be considered a design technique and not a theory. Since "a period of developing technique necessarily precedes periods of consolidating theory, whether the subject be physics, mathematics, biology or computer science," computing is in the beginning of its journey (Forsythe, 1967, p. 5). Forsythe compared computer science to early engineering or mathematics after Newton, arguing that the present stage was a passing stage for computer science.

Donald Knuth directly addressed the relationship between the art and the science of computing in his Turing lecture, "Computer Programming as an Art." After doing a little bit of research, he discovered that arts are related to technology, and more broadly, the application of knowledge. Art may use knowledge from a number of sciences, yet many sciences strive to move beyond the art stage, to becoming a science (Knuth, 1974). Knuth concluded that "science is knowledge which we understand so well that we can teach it to a computers; and if we don't fully understand something, it is an art to deal with it" (Knuth, 1974, p. 668). Even though computing had come a long way by 1974, he admitted that "nearly everything [computer scientists] do is still an art" (Knuth, 1974, p. 669). Computing is an art because it "applies accumulated knowledge to the world, because it requires skill and ingenuity, and especially because it produces objects of beauty" (Knuth, 1974, p. 673). Knuth believed that a programmer must see him or herself as an artist, and only then could he or she enjoy computing and do better work. In other words, he believed that art is inherent in every science, and particularly in computer programming, where art and science complement each other.

Computing as Engineering and Technology

Even though computer scientists have shared an understanding of the artistic aspects of computing, their views on engineering and science of computing have often diverged._Richard Hamming believed that the field of "computer science" should be more accurately labeled as "computer engineering" (although he did not advocate the change in name) because the subject dealt with not what is possible but rather with finding a practical working system, an algorithm, a scheduler or compiler for a reasonable cost of both time and effort (Hamming, 1987). Forsythe (not a Turing Award winner) was not willing to take sides (science or engineering). Instead, he described computer science as being both abstract (science-like) and as pragmatic (engineering-like). The "abstract" corresponded to the medium of computer science—the information, the meaning of symbols and numbers. More importantly, similar to those of mathematics, one of the goals of computer science was to "create a basic structure in terms of inherently defined concepts that is independent of any particular application" (Forsythe, 1967, p. 2). The "pragmatic" component corresponded to economic questions pertaining to the relationship among the speed, accuracy, and cost of computation as well as the organization of the hardware and software. Similar to mathematicians, computer scientists insisted on "high standards of rigor and exposition" (in mathematics terminology), or "performance and documentation (in computer science terminology), and placed a higher premium on quality than on promptness" (Forsythe, 1967, p. 5).

Juris Hartmanis also argued against separating computer science from engineering because computing is very much focused on "how" and is "intertwined and permeated with engineering concerns and considerations" (Hartmanis, 1994, p. 41). However, it is not a sub-branch of engineering; it is a new form of engineering and "an independent new science" that Hartmanis called the "engineering of mathematics" (Hartmanis, 1994, p. 41). The search for science is a search for generalizations and general constructs that are somewhat different from particular aspects of engineering. For computing to become a science, a niche had to be carved "away from specific applications and away from specific machines" as well as "away from specific programming languages and operating systems”—this separation was and still is “a condition *sine quo non,*[46]” according to Dijkstra (1986, EWD952).

Computing as Mathematics

In Dijkstra’s perspective, computer science was mathematical. He predicted that “mathematics will emerge as the art and science of effective formal reasoning” (Dijkstra, 1989, EWD1051). Dijkstra noted that even though computing is a mathematical science, “mathematicians and computing scientists live in different worlds,” and since they do not speak to each other, he tried to bridge the disciplines of mathematics and computing (1985, EWD917). For him, “the beauty of a program” was similar to “the beauty of a proof,” and this similarity “provided an emotional link between two at that time rather disjoint cultures [mathematics and computing], a link that may very well have had a decisive influence” (Dijkstra, 1976, EWD566). Both Dijkstra and Hartmanis believed that computing someday could give something back to mathematics, the discipline that originated it, by realizing Leibniz’s Dream of performing “symbolic calculation as an alternative to human reasoning” (1988, EWD1036).

Richard Hamming, then the head of the Numerical Methods Research Department of Bell Telephone Laboratories, saw more differences between the two disciplines of mathematics and computer science. Surely mathematical taste consists of such intangibles as elegance and deep results, but it is less pertinent in computing. He observed that some parts of mathematics are an “art form” because they do not deal with “noise” (which is part of real world). Having acquired experience in working with mathematics on computers, he argued that mathematics often “ignore[s] the careful examination and exposition of the methods it uses” (Hamming, 1965, p. 474). Surprisingly, this is where Dijkstra agreed with him, stating that the “problem with today’s mathematical curricular is that mathematical results are published and taught quite openly, but how mathematics is done is not published, not taught explicitly, and the

[46] “Without which [there is] nothing” (Latin).

student must pick it up by osmosis so to speak (1975, EWD512). While mathematicians value the exactness of their statements and the rigor of their results, they are not explicit about how one goes about deriving them (neither do they deal with imperfections and discreteness found in the real world). In that respect, Hamming argued that computing had to be more clear and precise with the process used and as a result, the goals and objectives of computing were more aligned with scientific culture than with mathematics.

Computing as a Language and a Human Activity

Besides mathematics, the central activity of computing—the programming—makes extensive use of languages. A number of Turing Award winners received their awards for designing and developing new languages. Languages are an intermediate[47] layer, a useful way to mediate between human commands and computer computational logic, the world of control, representation, and execution. Languages are used to write programs (software) that get translated into computable form interpreted by computers. Although mathematical notation is perhaps "the best-known and best-developed example of language used consciously as a tool of thought," it has serious deficiencies (Iverson, 1979/1987). Kenneth Iverson argued that even mathematical notations lack universality and may have different interpretations. The requirements for computer languages are also demanding. Efficient languages have to offer precision, expression, power, simplicity, performance, and the ease of manipulation in order to aid programmers in writing programs (Liskov, 2008/2010). "Programmers think of programs in terms of programming languages," described Barbara Liskov (2008/2010). Early on, languages were less precise, but with time, they evolved to approximate mathematical objects. Languages are control structures such that by designing a language, one gives but also takes away from users "the expressive power" (Liskov, 2008/2010).

[47] Languages are noted to supply "the metaphysical and physical contexts in which mathematics operates" (Knoespel, 1987, p. 40).

Computing as Science[48]

Newell and Simon also considered computing a science because it had a strong experimental component but defined the subject more broadly as “the study of the phenomena surrounding computers” (1976, p. 113). They argued that computer science is an “empirical inquiry” in which each new machine and program is an experiment posing a question to nature, whose answer comes from “observing the machine in operation and analyzing it by all analytical and measurement means available” (1976, p. 114). By adopting an empirical approach, computing had become more scientific.[49] However, not everyone agreed with this approach.[50] Naur held a different perspective on what made computer science a science. He considered the issue not to be “fields of insights or problems, but rather a manner of dealing with certain issues of insights, the scientific manner” (1992, p. 55). He argued that the central activities of computer science consisted of the design and building models:

> A prominent part of computing is the activity of designing, building, and making use, of constructed models in the form of programs running on digital computers. In fact, if extended to include supporting activities, model building can be seen to embrace virtually all the activities commonly included in computer science, data processing, and computer software and hardware development. (Naur, 1990/1992, p. 55)

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[48]Not all computer professionals embraced the science of computing. Programming skills are often obtained without the study of scientific principles, leading to the alienation and underutilization of scientific achievements. Dijkstra made an observation that in the 1980s practitioners (computer professionals commonly working in industry) were not using nor were they aware of the many developments and achievements in academic computer science (1985, EWD917). Practitioners believed that the science of computing had little to offer, while Dijkstra argued that computer science could have saved corporations millions of dollars. From this perspective, computing was no different from engineering in the late 19th century and the disdain for academic engineering among practitioners who thought that newly invented engineering science had little to contribute to everyday practice where common sense could suffice (Calvert, 1967).

[49] Mathematics, on the other hand, is not an empirical science, yet it is closely linked with natural sciences. This observation about the “double face” of mathematics was made by John Von Neumann, see Naur, P. (1975). Programming Languages, Natural Languages, and Mathematics. *Communications of the ACM, 18*(12), 676-683.

[50] The process of observing programs did not seem to be fruitful to Dijkstra and other researchers. Since machines had not yet learned to “think,” Knuth described that they did “exactly as they [were] told, no more no less” (1968, p. v).

However, these activities could be done “without adopting a scientific manner or work,” which is what seemed to be happening in computing because many published contributions lacked “due scientific investigation” (Naur, 1992, p. 56). Furthermore, since hardware and computer languages, in his opinion, had been invented, he argued that the activity of “invention in computing” was problematic because it could not “in itself qualify as a scientific activity” (p. 56). Naur’s concerns were shared by other Turing Award winners. Computer science, argued Dijkstra, dealt “with a world of artifacts in which the complexity [was] of our own making” (1986, EWD952), and thus the core challenge facing computer scientists was “how not to make a mess of it” (1989, EWD1051). Fred Brooks made a similar point by comparing artifact-building practices in computer science to the natural sciences: “When one discovers a fact about nature, it is a contribution per se regardless of its size. Since anyone can create something new [in computer science], that alone does not establish a contribution. Instead, one must show that the creation is better” (qtd. F. Brooks, National Research Council, 1994, p. 35).

Using some branches of mathematics, computing strives to be a science by not only appending the word “science,” as Alan Kay observed, but also recognizing its own uniqueness (Kay, 2003). One of the unique characteristics of computer science is that it deals with matter that is not directly governed by physical laws, as described by Juris Hartmanis in the following excerpt from his Turing lecture:

> Computer science differs so basically from the other sciences that it has to be viewed as a new species among the sciences, and it must be so understood. Computer science deals with information, its creation and processing, and with the systems that perform it, much of which is not directly restrained and governed by physical laws. Thus computer science is laying the foundations and developing the research paradigms and scientific methods for the exploration of the world of information and intellectual processes that are not directly governed by physical laws. This is what sets it apart from the other sciences and what we vaguely perceived and found fascinating in our early exploration of computational complexity. (Hartmanis, 1994, p. 39)

The other defining characteristic of computer science, as expressed by a number of Turing Award winners, was its use as a tool for simulations that could become a new source of scientific knowledge (Simon, 1996). In his book, *The Sciences of the Artificial,* Herbert Simon (1969/1996) placed computer science into the category of an “artificial” science—the science of design and abstraction, which is “akin to the science of engineering—but very different” (Simon, 1969/1996, p. 5). Simon advocated a multidisciplinary approach to the emerging “science of design” (concerned with creating artificial things), in which various disciplines (including computer science) work together and use computers as a primary tool of the design process (Simon, 1996, p. 137).

CONCLUSION

In this chapter, I reviewed the history, formation, and the nature of the field of computing. In regard to the first question on valued contributions (also see chapter 4), I found that even the elites of computer science, Turing Award scientists, did not always agree on the defining characteristics of their discipline. The struggle of computer science to define itself was noted by other researchers (Ceruzzi, 2003; Pollack, 1982) who acknowledged “almost chaotic diversity” of early perceptions of computer science (Pollack, 1982, p. x). The ACM helped to define computer science as a mathematical and theoretical science (and less so the study of hardware). Computer science evolved into what some Turing Award scientists (Herbert Simon, Alan Perlis, and Allen Newell) argued it was not –“the study of algorithms, with a focus on the even narrower field of programming languages” (Ceruzzi, 2003, p. 102). Nevertheless, the writings of Turing Award winners have provided insight into the nature of computer science as comprising of both science (as both a mathematical and abstract endeavor) and engineering (as both an empirical and pragmatic activity), and possessing elements of a craft, an art, and languages. Computer scientists have argued that in their discipline, science and engineering were closely intertwined, forming a delicate balance (which can also become a source of tension), and thus separating science from technology is futile. Computer science combines both science and technology to create a new breed of science, the science of the artificial (“man-made as opposed to natural,” see Simon, 1996, p. 4).

The history and the formation of the discipline provides insight into the second question of this study pertaining to the prominence of certain educational institutions (see chapter 5) and the demand for computer professionals in specific sectors such as military and business (see chapter 6). First, we learned that the institutionalization of computer science on university campuses was gradual and took various forms and titles—in some cases the department was joined with engineering and in other cases with mathematics. Five schools figured prominently as early pioneers: MIT, the University of Pennsylvania, Harvard University, Princeton University, and Columbia University (Aspray, 2000) but later dominance was shared with Stanford, Carnegie Mellon University, and Cornell (Goldberger, Maher, & Flattau, 1995). Second, computing in the U.S. developed in the middle of the 20th century under the auspices of military and business corporations that fostered research, education, by providing equipment and job opportunities, and, in addition to academia, gained prominence as sites of research and knowledge production.

Computer science is one of the few disciplines that formed rapidly in the last seventy years and embraced strongly both science and engineering.[51] Because of its new and amorphous nature, computer science is a "strategic site" for the analysis of what makes some contributions prize-worthy, how contributions are judged in a new field, and what standards and values peers use in their evaluations. Having reviewed the observations of Turing Award winners on the defining characteristics of the field and their activities, we may conclude that "important technical contributions" that define the discipline can vary (reflecting values associated with art, craft, mathematics, engineering, and science). Specifically, Turing Prize winners acknowledged that contributions to computing can be made without adherence to scientific methods (as a craft). In addition, since inventions in computing do not by themselves constitute a contribution, a researcher (and certainly the award committee) needs to demonstrate the merits of his or her invention. These observations call for an investigation of the kinds of contributions

[51] Historically, science and engineering/technology have been two different communities, "each with its own goals and system of value"[51] (Layton, 1971, p. 565). Nevertheless, the knowledge that scientific and technological communities generated flowed in both directions: scientists played a vital role in the emergence of engineering science [51] while engineered machines helped to propel science. Eventually, the American technological community became "a mirror-image twin" of the scientific community (Layton, 1971, p. 575). In the 1980s, researchers had already been "less prone to think in terms which subordinate technology to science, [with] the former working out the implications of the latter" but recognized them "to be on a par with each other" (Barnes, 1982, p. 166). From a model of hierarchical dependence (in which technology is dependent on science), the relationship between science and engineering moved to an interactive model of "equals." Science no longer deals only with discovery and technology with applications; instead, both science and technology, which involve invention and process, make use of each other. More importantly, both science and technology build on prior knowledge (science mainly but not exclusively builds on scientific knowledge and technology builds on technological developments).

that were selected by the award committee, the scientists selected, and the methods of selection—the issues that I set out to investigate in this study.

CHAPTER 3

METHODS

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This study employs a combination of qualitative and quantitative methods to address two key questions: 1) Award-Winning Contributions: What are the valued characteristics of award-winning contributions to computing and the method of selection of these contributions used by the Turing Committee deciding on the award? 2) Education and Careers of Winners: Which factors (educational and career-related, including collaboration) are associated with the winners of the Turing Award and differentiate them from the control group of non-winning computer scientists?

The first question is addressed with content analysis of award citations and analysis of archival documents of the association giving the award, the Association for Computing Machinery (ACM). The content analysis of award citations makes it possible to assess the characteristics of contributions by type (based on the activities of contributors) and by identifying areas and subareas of contributions. Archival documents are important primary sources of evidence of the procedures that the Turing Committee follows in identifying the most salient contributions. The documents provide insights into the nomination and selection processes, the standards, values, and the criteria for the assessment of the contributions. The second question is addressed with a mixed method approach that includes a) descriptive statistics and a correlation analysis, b) logistic regression analysis, and c) a method of qualitative comparative analysis (QCA). The data for the second question consist of biographic information and bibliometric statistics retrieved from the Thomson Reuters' Web of Knowledge, *Science Citation Index*. Because "purely quantitative approaches cannot capture the richness of individual career paths" (Cole [1987] qtd. in Sonnert & Holton, 1995b, p. 33), quantitative analysis (regression) is complemented by a qualitative comparison of cases and, where possible, excerpts from personal memoirs, award presentation lectures of Turing Award winners, oral history interviews with Turing Award winners (in most cases within a few years of their award), and several other interviews with ACM officers, conducted between 2004 and 2009.[52] Although this research project could not make extensive use of memoirs, oral history interviews, and other personal accounts, these materials informed the "narrative of variables" by revealing the narrative of individuals and the complexity and the trajectories of their careers (see Abbott, 1992).

I. FIRST QUESTION – THE AWARD-WINNING CONTRIBUTIONS: VALUED CHARACTERISTICS OF AWARD-WINNING CONTRIBUTIONS AND THE METHOD OF THEIR SELECTION

A. Data

Award Citations

I retrieved the citations for the Turing Award winners from the Association for Computing Machinery (ACM) website,[53] which maintains a list of all awardees. Each short citation typically contained a paragraph-long description of the contribution(s) for which the person was awarded the prize. Award citations were the primary sources for the analysis of valued characteristics of contributions.

Archival Data

I undertook the archival research to understand affiliations of Turing Award scientists with the ACM. The available documents contained communications regarding both the selection of Turing Award winners and their subsequent participation on the committee responsible for the selection of new winners. The archives had substantial data on nomination and selection criteria used by the Turing Committee. The documents relevant to first question primarily came from two archives[54]:

1) The University of Michigan Bentley Historical Library

[52] The ACM and Charles Babbage Institute (CBI) have been making great strides in archiving the history of computing. Some earlier interviews with Turing Award scientists were also available.
[53] Retrieved in September 2008 from http://awards.acm.org/homepage.cfm?srt=all&awd=140
[54] The visits of these archives were made possible through a fellowship awarded by ACM and later a travel grant awarded by CBI to investigate links between Turing Award winners and the ACM for which I am very thankful.

The Bentley Historical Library contains the collection of papers of Bernard A. Galler (1956-1994), president of the ACM from 1968 to 1970 and a member of the Turing Award Committee (more than once). In addition, the collection contains important records from the Turing Award Committee (1971-1979, 1988-1989, 1990-1992), a larger Awards Committee (1977-1978), and various other award nominations (1974-1984, 1971-1992). The records of the Turing Award Committee were the most useful sources of information because they contained a series of communications discussing nominations, award criteria, and voting on Turing Award winners.

2) The Charles Babbage Institute (CBI) at the University of Minnesota

The CBI contains ACM organizational records (1967-1978), nominating committee records (1975-1978), and other organizational and management-related records (1971-1973, 1980-1985) from the headquarters of the ACM. The ACM records aided in understanding the development and professionalization of computing from 1947 to 2003 (see Chapter 2).

In the two archives, the most pertinent records were those pertaining to the work of the Turing Award Committee (nominations and selection correspondence), which covers a time period of about two decades from 1971 to 1977 and from 1980 to 1992. The actual scoring sheets of the committee were available only for certain years, 1973-1976 and 1992. The selection process and voting procedures, as other organizational routines, remained similar from year to year. The archival records from the Turing Award Committee, although incomplete, illustrated the communications and the decision-making process that the Turing Committee followed. The process of decision-making helped to identify the characteristics of the contributions that the committee considered important.

I also used some materials from the Center for American History at the University of Texas at Austin and the Stanford University Archives. The archives at the University of Texas at Austin contain a collection of papers by Edsger Wybe Dijkstra (1930-2002), a Turing Award winner and one of the most influential computer scientists. The collection contains documents about Dijkstra's professional career and personal life, his curriculum vitae, diaries, correspondence, honors, and papers pertinent to the Turing Award from

1972 on.[55] The Stanford University Archives collection contains the papers (1953-1998) of Douglas C. Engelbart, the Turing Award winner from 1997, and Edward A. Feigenbaum, the Turing Award winner from 1994. These collections include their professional papers, correspondence, research proposals, technical reports, notes, journals, and valuable patent information. The materials from these archives were mainly used for chapter 2 on the formation, history, and nature of the field of computing.

B. Variables

To identify valued characteristics of contributions, I used the award citations and the archival records of the Turing Award Committee related to the nomination procedures and selection criteria. When examining the award citations, the variables of interest were the *subject area* and *sub-area* of the contribution and the *type* of contribution accounting for what the winners actually did, that is, if the winners invented, developed, implemented, or published something. In addition, archival records provided clues about what the committee had considered a valuable contribution and the *criteria* and *procedures* used to evaluate candidates.

C. Methods Of Analysis

Award citations were analyzed using the techniques of qualitative research (Maxwell, 2005) by 1) identifying up to three contributions within each award citation; 2) finding appropriate subject areas in the ACM Computing Classification System[56] (used to classify publications in ACM journals); and 3) using thematic coding to identify common categories for the type of contribution specified in award citations. I identified subject areas and types of contributions, sorted and counted them, and created graphs and tables summarizing the characteristics of the contributions. These, I present in chapter 4. The validity of classification within the ACM Computing Classification System was verified by consultation with a Georgia Institute of Technology senior professor, Dr. Marilyn

[55] Most of Dijkstra's writings, commonly known as EWD, have been digitized and are available online at http://www.cs.utexas.edu/~EWD/ .

[56] ACM Computing Classification System accounts for all topics in computing (valid from 1998 through 2010). See http://www.acm.org/about/class/ccs98-html

Wolf, Rhesa "Ray" S. Farmer Distinguished Chair of Embedded Computing Systems. The consultation helped to narrow down areas of contribution (in some cases all contributions belong to only one area as opposed to two or three areas).

The discovery of archival documents related to nomination and selection procedures was valuable. To facilitate the review of these materials, archival photocopies were printed, stamped with the location and the date (if necessary), and organized into two binders: 1) a binder on the Turing Award Committee, covering materials from the 1960s through 1992, and 2) a binder with ACM and other archival records from the 1940s through 2004. Since “every social phenomenon, organization, or movement unfolds over time and space” (Hill, 1993, pp. 59-62), the binders were organized chronologically. By following chronologically ordered documents, I aimed to reconstruct and make sense of events, communications, interpersonal networks, and organizational linkages.

Archival records helped to identify the context, criteria, procedures, methods of nomination and selection used by the Turing Award Committee to select the award winners. Despite the limitations of archival analysis (gaps, fragmentation), archival research “holds the power to confirm as well as to disturb our collective legitimations” because archival discoveries are often “threatening to established reputations and the hegemony of the status quo” (Hill, 1993, p. 6). The results of archival analyses were the primary sources for chapter 4 on the award-winning contributions.

II. SECOND QUESTION – EDUCATION AND CAREERS OF WINNERS: FACTORS THAT DIFFERENTIATE TURING WINNERS FROM NON-WINNERS

A. Data

Biographical

I used the *Biography and Genealogy Master Index* database to identify available biographical publications for each Turing Award winner (1966-2008). For 51% of the cases, the same 25th edition of the biographical directory *American Men and Women of Science (2008)*[57] was used to ensure consistency of the biographical data since it contained the majority of the winners' biographies and was available as an online database. The biographies that were missing from the 25th edition were found in earlier printed editions: the 17th edition (1989-1990); the 13th edition (1978) for Social and Behavioral Sciences[58] (for Herbert Simon); the 5th edition of *Who's Who in Technology*: *Who's Who in Electronics and Computer Scien*ce (1986)[59] (for John Backus, Robert Floyd, and Alan Perlis); the 9th edition of *Who's Who in Science and Engineering 2006-2007*[60] (for Butler Lampson, Dennis Ritchie, Ivan Sutherland); 4th edition of *Who's Who in Engineering*, 1980[61] (for Fernando Corbato, Richard Hamming, William Kahan, Allen Newell); *Who's Who of British Scientists 1971-1972*[62] (for Maurice Wilkes); *Who's Who of British Scientists 1980-1981*[63] (for James Wilkinson); and *Who's Who in Science in Europe*[64] (the 3rd edition [1978] for Peter Naur and the 9th edition [1996] for Charles Hoare).

For the matching sample of scientists, that is, non-Turing awardees, I used the same 25th edition of the *American Men and Women of Science*[65] biographical directory, as well as earlier published editions of this directory (the 12th, 13th, 16th, and 17th editions); the 5th edition of *Who's Who in Technology*; *Who's Who in Electronics and Computer Science*, 1986; and the 9th edition of *Who's Who in Science and Engineering 2006-2007*.

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[57] Cengage Learning. (2008). *American Men & Women of Science. A biographical directory of today's leaders in physical, biological and related sciences* (25th ed.). Detroit: Gale.
[58] (1978). *American men and women of science: social and behavioral sciences* (13th ed.). New York: R. R. Bowker Company.
[59] (1986). *Who's who in technology: who's who in electronics and computer science* (5th ed.). Woodbridge, CT: Presearch Publications.
[60] (1992). *Who's who in science and engineering 2006-2007* (9th ed.). New Providence, NJ: Marquis Who's Who.
[61] (1980). *Who's who in engineering* (4th ed.), New York: American Association of Engineering Societies.
[62] (1970). *Who's who of British Scientists 1971-1972.* Athens, OH: Ohio University Press.
[63] (1980). *Who's who of British Scientists 1980/81* (3rd ed). Dorking, Surrey: Simon Books.
[64] (1978). *Who's who in science in Europe* (3d ed.). Guernsey, B.I.: Francis Hodgson.
[65] Cengage Learning. (2008). *American Men & Women of Science. A biographical directory of today's leaders in physical, biological and related sciences* (25th ed.). Detroit: Gale.

Biographical entries contain basic demographic data (date and place of birth, year of marriage, children) as well as career histories: information about education, work experience, memberships in professional associations, and honors received; data often used by researchers in the study of scientists (e.g., Long, Allison, & McGinnis, 1979).[66] Educational statistics, retrieved from the biographical entries of Turing Award scientists and the control group of scientists consisted of a) bachelor's, master's and Ph.D. institutions, b) fields of study and degrees (mainly the terminal degrees), c) work experience during graduate studies (fellowships or jobs), and d) years when degrees were received. Educational data retrieved from biographies was supplemented by additional information about the dissertations and advisors of Turing Award scientists collected from the first few pages of the dissertations available through the *ProQuest Dissertations & Theses* database. Additionally, the Acknowledgements page of the dissertations (if listed) provided information about the financial support of Turing Award winners during graduate school. Furthermore, through the Clay Institute's Genealogy project,[67] I was able to verify for most Turing Award winners a) the title of the dissertation, b) the Ph.D. institution attended, c) the Ph.D. year of graduation, d) the advisor's name, and, most importantly, the names of students trained by the same advisor. It was a serendipitous finding that the Clay Institute's Genealogy project included not only pure mathematicians but also scientists in areas of applied mathematics and computer science pertinent to this study.

<u>Bibliometric</u>

Biographical entries usually do not include information on the publications of scientists. That information (i.e., the number of publications,[68] the citation count of the

[66] Note: curriculum vitas would have been preferred but were not available for all winners because many winners were already very old and/or passed away.
[67] See http://www.genealogy.ams.org/
[68] The publications used in this study were only articles defined broadly (more precisely, all document types catalogued by the Web of Knowledge, Science Citation Index Expanded). I also collected information about books published by Turing and non-Turing scientists prior to the year of the award from the WorldCat Online Computer Library Catalog (OCLC) database. See a footnote in chapter 6 and Appendix G on publication practices in computer science.

most cited publication, and co-authorship) was collected from the Thomson Reuters *Web of Knowledge* (formerly the Institute for Scientific Information [ISI] *Web of Science*), the *Science Citation Index Expanded* (SCI-EXPANDED).[69] The *Web of Knowledge* provided bibliometric information about the publications and citations of Turing Award and control group students, and their shared advisors. For advisors, the number of publications and the highest citation count of one of the advisor's publications were collected for two time periods—up to the year of the doctoral degree awarded for a given Turing scientist and up to the year when the scientist received the Turing Award. The record of publications of Turing and matched scientists pertinent to this study was limited to up to the year of the award (and corresponding number of years for matched scientists), and consequently, publications that came out after the award were not considered.

Archival

The data on Turing Committee members came from two archives described above (Bentley Historical Library and the CBI). The documents contained a list of Turing Committee members from multiple years. This was a serendipitous source of data. The total of 42 members of Turing Committees were identified, three of whom served more than one term. I estimate that these 45 members represent about 96 percent of the 47 members who, according to my estimations, could have served five-year terms during the 43-year time period (1966-2008) covered by this study.[70]

Oral History Interviews and Biographic Remarks

The ACM Oral History interviews with Turing Award winners and ACM administrators were informative but not central to this study. Similarly, the lectures of

[69] See Appendix G on publication practices in computer science.
[70] The official archival documents indicated that the Turing Committee consisted of five voting members and added a new member each year while eliminating one former member. To calculate the total number of members who served on the committee, I assumed that the addition of members to the committee started during the second year of its existence. I counted 5 original members and 42 members added during the next 42 years (in addition to the first year). Thus, in total, at least 47 committee members served on the Turing Committee during the 43-year period (not counting early terminations and their replacements; no information was available regarding those).

Turing Award winners, published in the *Communications of ACM* (and partially as a book),[71] aided understanding by providing first-hand (written by Turing Award winners) testimony of computing careers and contributions. I referenced Turing Award lectures in the discussion of the nature of computer science when it was pertinent in chapter 2.

Group of Turing Award Scientists in this Study

The group of Turing Award scientists consists of all 55 Turing Award winners for the period from 1966 (the year of the first award) through, and including 2008 (43 years in total). The award is usually given to a single person, but on seven occasions, the award was shared by two scientists and twice by three. The group of Turing Award winners studied consists of 53 men and 2 women, 20 (36%) of winners were foreign born while the remaining 35 (64%) were born in the U.S. Out of the 55 awardees, 12 (22%) were educated abroad and the remaining 43 (78%) in the United States. Although many Turing Award scientists were quite mobile,[72] moving from one institution/country to another, two dominant groups were discernable among Turing Award winners: American scientists (those who were educated in the U.S. and worked in the U.S. regardless the place of birth) and foreign scientists (who were born, educated and worked primarily abroad, especially at the time of the award). Citizenship information was available for some cases in biographical records. Additionally, work history in the United States at the time of the award provided some evidence of the immigration status, though the available data does not allow accurate assessment of the true naturalization/immigration status of these scientists. In particular, the naturalization status was not clear for Canadian scientists, who may have obtained permission to work in the United States while remaining Canadian nationals.

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[71] Association for Computing Machinery [ACM]. (1987). *ACM Turing Award lectures: the first twenty years, 1966 to 1985*. New York: ACM Press.

[72] Eminent scientists tend to be geographically mobile, working and traveling between different countries. The data collected confirm that we are dealing with a world that extends especially across the US, Canada, the UK, the Netherlands, Norway, and Israel. Hence, it can be referred to as a “transatlantic world.”

The heterogeneity of the Turing Award winners raised some concerns regarding inferences about Turing Award winners as a group across a diverse multinational population, particularly when designing and interpreting the results of inferential statistical analyses. Using descriptive statistics, I decided to summarize the information about the contributions and the educational background of all 55 awardees. However, I could not use all 55 awardees for the inferential analyses. The education and the careers of foreign Turing Award winners took place in cultural and economic systems different from those in the U.S. with regard to patterns of employment (e.g., working many years for one employer), performance standards, and rules for advancement. The effect of independent variables on the outcome of winning the Turing Award is likely to be subject to environmental influences of culture, gender, or educational credentials, and the effects of these factors should be isolated. One of the methods of isolating studied effects in science is to remove or hold constant extraneous factors and examine the effects "within constant values of other potential causes" (Cohen, Cohen, West, & Aiken, 2003, p. 455). Therefore, foreign scientists (introducing new extraneous cultural factors) were not suitable for inclusion in the comparative analyses of winners and non-winners (American scientists) and their career attainments. In an effort to ensure comparability and interpretability of results, I limited the comparative analyses of winners and non-winners to only American winners with a Ph.D. who were matched with a control group scientist trained with the same advisor. The comparative analyses (of education and career attainments which included correlation analysis, logistic regression and QCA) of winners and non-winners excluded (and in some cases addressed separately): 1) foreign scientists (N=14), 2) a few scientists without Ph.D.s (N=5) and those with a Ph.D. with only industry work experiences (N=3), 3) American women scientists (N=2), and 4) one (N=1) American social scientist.

First, fourteen foreign-educated scientists were excluded from comparative analyses (but included in the analyses of educational pathways using descriptive statistics) because they could not be compared to U.S. scientists and engineers since 1) their graduate and work institutions were not part of the chosen ranking and thus their status could not be easily compared; 2) it was not possible to identify a match (non-winner) for these scientists using the same procedures; and 3) these scientists were employed in at least one or more counties that had different economic, social, and cultural expectations for promotions and rewards for scientists than those in the United States.[73]

Second, academic and industry scientists often differ in education attainments. Computer scientists in industry often have just a master's degree (four Turing awardees), while a few have earned a Ph.D. (three Turing awardees). The variations between academic and industry career paths (norms, expectations, productivity) are substantial (Dietz & Bozeman, 2005). In order to hold constant (to the extent possible) the educational and career paths of the studied scientists and facilitate their comparison, I decided to exclude winners without a Ph.D. (N=5, four of whom were industry scientists) and those with only industry experience (N=3) with a Ph.D. I address the career paths of industry scientists with a Ph.D. separately in Appendix B. The careers of industry scientists are not less important, but the criteria of success outside of the academic setting were more diverse, reflecting the variety of organizational norms and positions in which the scientists were employed (also see Sonnert & Holton, 1995a, p. xiv). In order to have a basis for comparability, I retained winners with a Ph.D. with academic and mixed backgrounds (academic and industry).

Third, I excluded and addressed separately in the Appendix C the cases of two women Turing Award winners, for whom data were likely to be influenced by broad implications of gender (interactions of gender and career achievements).[74] Fourth, one computer scientist (Herbert Simon), trained in the social sciences, was excluded because I could not find a comparable match for him. As a result, the group (N=30) of Turing Award winners included in the comparative analyses is comprised of academic (and

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[73] For the description of American society, see Williams, R. (1955). *American Society.* New York: Alfred Knopf. For the description of American science, see Cole and Cole (1973).
[74] On average, women in science have lower publication productivity (Cole & Zuckerman, 1984; Xie & Shauman, 1998) and visibility (Long, 1992) than men. It takes women longer to achieve academic ranks (Cole & Zuckerman, 1984) and compared to qualified men, they are promoted more slowly (Long, Allison, & McGinnis, 1993; Sonnert & Holton, 1995b). A smaller proportion of total women scientists, compared to men scientists, appear among the high achievers in the extreme right-tail of the distribution of publication productivity (see, for example, Fox, 2005).

semi-academic) Ph.D. male scientists trained in the United States (29 Americans of which 24 were American born and five were naturalized and one Canadian [born]), and a comparable sample of matched scientists (N=30) described below.

B. Sampling

<u>Matching Sample of Non-winning Scientists</u>

The Clay Institute's Genealogy project website[75] was a useful resource that provided information about advisors and students of Turing scientists. For each Turing awardee, I identified a group of students who had the same advisor as a given awardee and who had graduated within five (5) years before or (5) years after the Turing Award winner (the first eligibility rule for inclusion in the matched sample). For the few cases in which no students had graduated within a +/-5 year time frame, I chose the person closest in time match, who could be classified as a computer science professional (see below).

To choose a match within the eligible cohort of the Turing Award scientists, I used the website *www.random.org*, which generated a random number out of N candidates. The random number determined which person would be picked as a match from the list of eligible students (first eligibility rule). For the matched scientist, the second eligibility rule was that a person had to have some affiliations[76] with the field of computer science to be considered for comparison (that is, have any work experience in the computer science field, membership in ACM, and/or awards in computing or ACM) regardless of his terminal educational degree. I used the *American Men and Women of Science* biographical directory to look up the biographies and the work areas of eligible matched scientists. Scientists bearing no computing affiliation (or without a single biography in the *Biography and Genealogy Master Index* database, which would indicate

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[75] See http://www.genealogy.ams.org/

[76] In the late 1960s and 1970s, scientists needed to "elect" computing (then, a new, emerging field) as their research area to become potential awardees. Some non-Turing scientists might have pursued traditional research in physics, engineering, or mathematics. Thus, identifying the opportunities to join the research in computing, which is a necessary condition to be an awardee, becomes important.

the absence of a professional career) were eliminated from the eligible cohort of matching scientists. For instance, I excluded those who had a degree in engineering if no links with computing or participation in ACM appeared, and this resulted in another random draw. The final eligibility rule for the matched sample was gender. Since I excluded the two women Turing Award winners,[77] I also left out women from the matching sample.

The matching design allowed partial control of certain individual factors (family socioeconomic status, parents' profession, pre-college and undergraduate education) distinguishing Turing scientists from non-Turing scientists.[78] This matching assured that two given scientists (an awardee and a non-awardee) shared educational conditions, and some presumed chance of making an important contribution and receiving the Turing Award.[79] Thus, the control group is composed of Ph.D.-level scientists with similar pre-requisites: training in the same field at the same institution and working with the same advisor within the same time period as the Turing Award winners—but with different career outcomes in non-receipt of the key award.[80]

C. Variables

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[77] These two cases are addressed separately in the Appendix C.

[78] I found no discernable differences in undergraduate institutions attended by winners and non-winners (see footnote in chapter 5). Unfortunately, the data on social origin of studied scientists were limited. It is known that eminent scientists tend to come from higher social classes (professionals in particular) and thus social origin is likely to facilitate (but not to determine) scientific recognition (Choobbasti, 2007). Zuckerman's study of Nobel laureates acknowledged that "the family origins of American laureates were much higher in rank than those of the population at large" (1977, p. 65). Nobel laureates were more likely to come from professional families and have fathers in business. Another study by NSF concurred that the "level of educational attainment for families of doctorate recipients is higher than the national average" (NSF, 2006, p. 24). Although data on the families of origin of Turing Award scientists were difficult to obtain, the available data seems to follow the same pattern. For twenty-five Turing scientists (45% of total 55) I was able to collect the occupation of their fathers from a variety of sources (biographies, autobiographies, Wikipedia). Among the 25 occupations of the fathers of (25) Turing Award scientists, 11 (44% of 25) can be classified as "professional," five (20% of 25) as "business," five (20% of 25) as "military," and four (16% of 25) as "others." It is worth noting that seven (28% of 25) occupations in the "professional" and "other" category were related to teaching.

[79] This also implies that productivity differences are less likely to be due to graduate university or advisor.

[80] The years of publications and employment for the matched scientists were calculated based on the year since their Ph.D. plus the same number of years of professional work as the corresponding Turing Award scientist (years from Ph.D. to the receipt of the Turing Award). The matched scientists also had as mixed academic and industry experiences as the Turing Award scientists.

I obtained the data on education, work, and professional associations from biographical and bibliometric records and coded the data into variables, listed in Appendix D. Of these variables, a small number of biographical and bibliometric variables was chosen for statistical analyses for reasons described below. In all analyses, the *dependent* variable was the recognition outcome of "winning a Turing Award" (1), compared to "not winning" (0). The *independent variables*, covering educational and career factors, consisted of *early career advantages*, *rate of publications*, *maximum citations*, *number of collaborators*, *type of collaborators*, *number of awards*, *location in an elite institution*, and *visibility in ACM* (see Table 3.1). Given the modest number of cases in each group (N of awardees=30, N of non-awardees=30), the number of independent variables to be tested together had been reduced to seven (however, nine variables were considered). The information about the rankings of academic institutions appears in Appendix E.

Education

1. Early Career Advantage

The converging educational patterns of elite scientists have been reported by previous empirical studies (Cao, 1999; Zuckerman, 1977). The importance of educational settings is conveyed by scientists themselves who particularly acknowledge "the quality of regular science instruction, peers' attitudes toward scientific or academic excellence, fellowships and financial support, mentors and role models, and special educational environments" (Sonnert & Holton, 1995a, p. 166). As a result, fellowships were included in the present study as a special type of reward as opposed to research assistantships that were more common (see Gaughan & Robin, 2004; NSF, 2006). Publications with mentors/advisors have been found to positively affect scientists' subsequent productivity (Long & McGinnis, 1985) and later career placement (Fox, 2003; Crane, 1965; Zuckerman, 1967). The rank of the doctoral department and sponsorship by the mentor (and not simply publication productivity) also influence the prestige and location of a scientist's first job (Cole, 1979; Long, Allison, & McGinnis, 1979). Evidence from multiple studies confirms that most prestigious departments mainly hire graduates from similarly prestigious departments and hires are not based simply on prior productivity (Burris, 2004; Crane, 1970; Long, 1978; Long, Allison, & McGinnis, 1979; Long & McGinnis, 1981). In addition, elite departments are more likely to hire their own Ph.D.s for some period of time (Burris, 2004; Hargens & Farr, 1973; McGee, 1960). Thus, mobility in academia is "mainly horizontal or downward and seldom upward" (Burris, 2004, p. 249). A number of studies successfully used the prestige of a first job to predict the prestige of a current job (Cole & Cole, 1973; Long, Allison, & McGinnis, 1979). Based on these findings, I decided to count the prestigious first job as an early career advantage.

An early advantage index was created by counting three types of advantages: a) graduate fellowships, b) publications with advisors during or right after one's doctoral study, and c) a first job at one of the top five computer science departments (Stanford, Massachusetts Institute of Technology, University of California-Berkeley, Carnegie Mellon University, and Cornell University). Each case was assigned a score from 0 to 3. An early career advantage score is a uni-dimensional scale that measures one underlying concept of early advantage on a single continuum from low (0) to high (3). Each measure (a graduate fellowship, a publication with an advisor, a first job in an elite [top 5] department) in the scale represents an advantage that is likely to increase a scientist's productivity and career success that later might be rewarded with an award. Each of the three advantages is treated as an approximately equal measure of "advantage" because it is not known how much each contributes to career success or weighting.[81] Thus, these variables are entered into the regression as a composite score.

<u>Career Attainments</u>

2. Publication Productivity

Publication productivity, measured by the rate of publications, was found to be the best predictor of how peers judge fellow scientists (Cole & Cole, 1973; Sonnert, 1995c). Positive evaluation based on the publication productivity rate is consistent with prior observations that eminent scientists tend to be productive researchers (Allison & Stewart, 1974; Fox, 2005; Reskin, 1977; see also review by Fox, 1983). High research

[81] Weighting would impose differential emphases that currently cannot be assigned accurately.

Table 3.1. Independent Variables Used for Comparative Analyses

Predictor Variable	*Operational Definition*	*Coding*	*Source of Data*
Educational Factors			
1. Early Career Advantage			
a. Early career advantage score	Early advantage in the form of a graduate fellowship, publication with the advisor, a prestigious first job in the top five computer science departments (Stanford, Massachusetts Institute of Technology, University of California-Berkeley, Carnegie Mellon & Cornell University).	Composite score (0-3) based on graduate fellowships, publication with advisor, first job in elite department.	Biographical record. The top five departments were selected based on National Research Council (NRC) publication (Goldberger, Maher, and Flattau, 1995). The top five universities remained the same in 1970s-1990s.
Career Attainment Factors			
2. Productivity			
a. Rate of publications	Number of publications prior to the Turing Award year divided by number of years since Ph.D.	Numeric	Web of Knowledge
3. Impact			
a. Maximum citations	The citation count of most cited publication prior and up to the year of the Turing Award.	Numeric	Web of Knowledge
4. Collaborations			
a. Number of collaborators	The number of co-authors prior to Turing Award year.	Numeric	Web of Knowledge
b. Type of collaborators	The number of coauthors already Turing Award winners (who did not share the award in the same year) OR coauthors members of the Turing Award Committee prior to Turing Award year.	Numeric	Web of Knowledge, Archives
5. Recognition/Eminence			
a. Awards	The sum of awards, fellowships, and memberships in NAE and/or NAS prior to Turing Award year.	Numeric	Biographical record, search on NAE and NAS websites
6. Institutional Location			
a. Elite Organization (Institution)	Employment in top five departments (institutions) for computer science at the time of the Turing Award.	1-Elite Org 0-Not Elite Org	Biographical record, NRC classification (see #1)
7. Visibility in ACM			
a. ACM visibility score	Publications in ACM journals; ACM awards; service positions in ACM; all prior to the Turing Award year.	Composite score (0-3) based on ACM publications, awards, and service.	Biographical record and Web of Knowledge

productivity typically involves a relatively high number of publications and contributions to multiple projects during a given period. By being prolific, a scientist can become visible and influential in the scientific community. Therefore, the rate of publications was chosen for predicting recognition in the form of the Turing Award. The count of publications prior to receiving the Turing Award (equivalent number of years was used for the matching sample) was retrieved from the *Web of Knowledge*. The rate of publications was computed by taking all of the publications and dividing them by the number of years between receipt of a Ph.D. and receipt of the award (or corresponding number of years for the matched scientists).

3. Impact

Since scientists cite colleagues' work for a number of reasons (Hargens, 2000), I decided to use the citation count corresponding only to the citations to a single most-cited publication received prior to the Turing Award (and including that year). Because award guidelines ask nominators to list a "specific" contribution that merits the award, the guidelines allude to the existence of an "outstanding contribution" that could have impacted the field in a major way (in a sense, was a "paradigm-shifter," Kuhn, 1962). A published contribution that had an impact on the community is likely to have a high citation count, and consequently, I collected citation counts to the most frequently cited publications. A maximum citation count consists of the total number of citations to a single most cited publication that a Turing Award winner received prior to (and including) award year.[82] As the citation counts were highly skewed, I applied a square-root transformation before entering them into regression.

4. Number and Type of Collaborators

To assess social capital of Turing Award and control group scientists, I used a count of collaborators (coauthors) on publications, collaborators who already won the Turing Award and collaborators who where members of the Turing Award Committee. I

[82] Because of the lag in publishing and award announcement, the citation count was not yet influenced by the celebrity status of the Turing Award winners after they received the prize.

retrieved the names of coauthors from the *Web of Knowledge* and identified the number and type of collaborators (other Turing Award scientists and members of the Turing Award Committee) of studied scientists. Since it was not clear which collaborators were most "useful" for receiving awards, in *Model 2,* I assessed effects on winning of all three variables: a) the total number of collaborators which presumably positively relates to the chances of being nominated for an award; b) collaborators who already received a Turing Award as they were likely to be asked to write recommendation letters; and c) collaborators with prior experience of serving on a Turing Award Committee whose sponsorship was not only beneficial but perhaps even critical for receiving a Turing Award.

5. Recognition/Eminence

Similar to other accomplished scientists, who typically receive awards (positive reinforcements) throughout their careers (Cole, 1979), Turing Award scientists are likely to have prior awards. Prior recognition and peer esteem, together with past successes, are likely to increase the probability of additional recognition. This phenomenon, known as *cumulative advantage,*[83] can operate together with the *Matthew Effect*[84] and may increase the chances of receiving the Turing Award for scientists already recognized by other awards. Consequently, I count the number of awards received prior to the Turing Award (or corresponding number of years for the matched scientists) as a measure of prior eminence. In addition, because induction into exclusive societies such as in the National Academies of Sciences or Engineering (NAS, NAE) marks exceptionally high status[85] and represents one of the highest achievements for U.S. scientists (Cole & Cole, 1973;

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[83] Cumulative advantage is the result of "the social processes through which various kinds of opportunities for scientific inquiry as well as the subsequent symbolic and material rewards for the results of that inquiry tend to accumulate for individual practitioners of science," see Merton (1988), p. 606.
[84] The Matthew Effect is "accruing of greater increments of recognition for particular scientific contributions to scientists of considerate repute and the withholding of such recognition from scientists who have not yet made their mark," see Merton (1968/1973, p. 446).
[85] Garfield (1977) found that the membership of Nobel Prize winners in national academies was very high (92%).

Feist, 1997), the induction into the National Academy of Science and Engineering was counted as an award if the year of induction preceded the Turing Award.

6. Institutional Location

Researchers have long established that being at a major university positively affects the likelihood of being recognized (Crane, 1965; Long, 1978). Scientists in prestigious departments also tend to be productive, as productivity conforms to the norms/standards of the department (Allison & Long, 1990). Being in a highly ranked department increases visibility in the research community, and, in fact, such location and individual's reputational successes have been found to influence each other (Cole & Cole, 1973). For these reasons, department affiliation during the year of the Turing Award is one of the most promising predictors of recognition and was included in the analyses.

7. Visibility in ACM

The Turing Award is presented by the Association for Computing Machinery and thus, visibility in the ACM is likely to be important for recognition. A high level of visibility through networking (interactions, communication, collaborations) was found to distinguish the careers of more successful compared with less successful scientists (Sonnert & Holton, 1995a). Professional organizations often become focal places for researchers' interactions and dissemination of new knowledge. Therefore, I computed visibility in the ACM measure/score based on three pieces of information: whether a scientist 1) had any publications in ACM journals, 2) had won any ACM awards, and 3) served in some capacity in the ACM (editor, administrator) prior to winning the Turing Award. Visibility in the ACM is a uni-dimensional scale that measures one underlying concept of visibility (on a single continuum from low [0] to high [3]). Each measure (i.e., ACM publication, award, and service) in the scale represents a connection with the ACM community (and thus is likely to increase one's visibility in the ACM community). Each item is treated as an approximately equal measure of visibility because neither the visibility measure nor the weight of each is known.

D. Methods of Analysis

My starting point is to summarize the gathered biographical and bibliometric data on Turing Award scientists with regard to their experiences in education, the job market, and the professional arena. The next task is to compare the two groups (awardees and non-awardees) with regard to the educational and career factors associated with recognition by the Turing Award. For that, I use variable-oriented (logistic regression) and case-oriented (QCA) strategies. While the variable-oriented strategy is "best suited for assessing probabilistic relationships between features of social structures, conceived as variables over the widest possible population of observations," the case-oriented strategy is "best suited for identifying invariant patterns common to relatively small sets of cases" (Ragin, 1987, p. 69). The advantages of using both approaches[86] are that the results present a "middle road" between specificity of cases and generalizations for the group, between human agency and structural explanations (Ragin, 1987, p. 71).

1. Descriptive Statistics

The data collected are summarized using descriptive statistics (frequency distribution and measures of central tendency and variation) and these data are used to construct a group profile of Turing Award winners in their age at the receipt of the award (chapter 4), origin and education (chapter 5), and careers (chapter 6). In chapter 6, career profiles aid the comparison of Turing and control group scientists.

2. Correlation Analysis and Logistic Regression[87]

Logistic regression is frequently used when the dependent variable is dichotomous (winning/not-winning an award) and the independent variables are of any type, which makes it a suitable analysis for conceptualization of dichotomous career

[86] During the ASA 2010 workshop on QCA, I asked Ragin about combining these two strategies. He had mixed feelings, saying that he had combined them but that he had not seen much merit in doing so because the two strategies differed in focus. Nevertheless, he published an article in which he acknowledged the merit of such approach, of using both a Boolean approach and logistic regression (see Ragin, Mayer, & Drass, 1984).

[87] If I were to ask about the distribution of chances of having a certain counts of awards, collaborators or publications, then a Poisson regression would have been an appropriate tool. Poisson probability distribution models the probability of counts of events in a given time period.

outcomes (see for example, Sonnert & Holton [1995b]). A multiple logistic regression procedure expresses the relationship between predictors and predicted probability of the outcome for which it derives an equation based on the magnitude of effects of independent variables and their contribution to the likelihood of the outcome. The resulting equation can also be used to predict the probability of membership of new cases in the dichotomous career outcome (Cohen et al., 2003). The advantages of logistic regression are that 1) this procedure is less affected than linear regression by the assumption of normality and equal variance/co-variance across groups (i.e., it does not assume homoscedasticity—equal variance of the residuals for all predicted values); and 2) it can handle categorical independent variables (Hair, Tatham, Anderson, & Black, 1998).

Prior to regression analysis, I obtained the measures of association (i.e., zero-order correlations) of eight interval and one nominal independent variables (see Table 3.1) with the nominal dependent variable (i.e., receiving/not receiving the Turing Award) in order to examine the strength of the (linear) relationships among these variables. Then, I used multiple *logistic regression* to assess the independent variables and seven hypotheses. To assess my research hypotheses and individual variables, I constructed five logistic regression models. I entered independent variables as a block in a series of steps (in SPSS "Enter" method) that assessed productivity measures as well as the contribution of collaborative and reputational variables.

Stepwise logistic regression was not the preferred method because this study is not "purely predictive research" or exploratory research with no concerns for causality (Menard, 1995, pp. 54-55). Prior studies in the sociology of science accumulated substantial findings that I used to create hypotheses (*H1-H7*) tailored to explaining recognition in science. Testing hypotheses based on existing theories (functionalism/universalism, cumulative advantage, social capital, logic of professions) provides grounds for new questions and more calibrated explorations in the future.

3. <u>Models of Recognition</u>

Recognition encompasses at least two social processes: nomination by peers and selection by the Turing Committee. Since the nomination procedures request a curriculum vitae (early on a bibliography was requested, see "Perlis Invited as A. M. Turing Lecturer for 1966; First Time ACM Honor is Bestowed," 1966) and letters of recommendation with a description of an accomplishment, the most central information for nomination can be narrowed down to three variables: scientific productivity (publication rate) conveyed by curriculum vitae, impact/quality of contribution (assessed by maximum citation) and likely to be noted in letters of recommendation, and the number and type of collaborators who were well-positioned to evaluate candidates and possibly write letters of recommendation. I assess these variables first in *Model 1* and *Model 2*.

a. Basic Model of Recognition

In the basic *Model 1,* I consider the most essential factors for being nominated for the Turing Award that are commonly used in the evaluation of scientists: publication rate and impact of their contributions (maximum citation). These productivity and impact measures assess scientific performance that is known to be the best predictor of judgments among scientists (Cole & Cole, 1973; Long, Allison, & McGinnis, 1979; Long, 1992; Merton, 1973; Sonnert, 1995c).

b. Basic Model of Recognition with Collaborative Variables

The second model, *Model 2*, adds and considers three collaborator variables: the number of collaborators and specific types of collaborators who would be most instrumental in supporting a candidate for the award—that is, collaborators who already received a Turing Award and collaborators who were part of the Turing Committee at some point prior to one receiving the Turing Award. This basic model with collaborative variables tests the effect and predictive power of collaborator variables in the absence of additional factors. While it is not known which collaborators may be influential in nomination, evaluation, and selection for the Turing Award, the collaborators who already received a Turing Award and collaborators who were part of the Turing Committee were most closely connected to the Turing Award and thus, were well positioned as evaluators or as supporters of Turing Award scientists. *Model 2* also includes the total number of collaborators because any one of those scientists is well positioned to propose a nomination and/or provide a recommendation letter. In fact, the greater the number of one's collaborators, the greater could be one's chances of being nominated. *Model 2* identifies[88] which collaborative variable (number of collaborators, collaborators with a Turing Award, and collaborators who were Turing Committee members) is most effective at predicting recognition, and whether hypothesis *H3a* or *H3b* should be further tested in other models (3-5) of recognition.

c. A Standard Model Without Reputational Variables

In *Model 3*, without reputational effects of awards and institutional location, I combine the basic model, the best collaborative predictor, and two new variables (early career advantage and visibility in ACM) to assess my hypotheses in tandem except for *H5* and *H6*. I decided to add the information about awards and institutional location separately in order to assess the effectiveness of new variables (early career advantage, visibility in ACM, and collaborative variable) in predicting the outcome of winning, independent of reputational variables that were likely to have a strong predictive power. The sequence in which independent variables were added was dictated by the logic of starting with the most essential variables for recognizing winners (based on their individual performance and impact) and moving to less essential variables.[89] Adding independent variables separately allowed the assessment of the effectiveness of several key variables: productivity and impact measures, collaborative variables, prior eminence (awards), and institutional location (in an elite university).

d. Two Standard Models With Reputational Variables

Model 4 with reputational effect, adds an additional variable, *awards*, to test the effect of awards on the standard recognition model. Finally, *Model 5* with reputational

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[88] The three collaborative variables correlate with other variables and should be examined with caution. The solution could have been to construct a composite index, but since I was interested in knowing which collaborators were most effective as a variable, I chose to include all of them in one logistic model.

[89] Some may argue that the (meritocratic) order can be reversed by stating that individual performance and impact are less essential since they are expected and that reputational measures are more essential because they indicate a person's stature within the scientific community.

effect, adds the final variable, *being in an elite institution,* to assess the contribution of institutional location to predicting the winner in the presence of the other factors. Table 3.2 summarizes the composition of each model.

Table 3.2. Proposed Models of Recognition

Model 1	Model 2	Model 3	Model 4	Model 5
Publication rate	Publication rate	Publication rate	Publication rate	Publication rate
Max citation	Max citation	Max citation	Max citation	Max citation
	Co-authors	Best collaborative variable	Best collaborative variable	Best collaborative variable
	Coauthors already Turing Award winners	Early advantage	Early advantage	Early advantage
	Coauthors Turing Committee members	Visibility in ACM	Visibility in ACM	Visibility in ACM
			Awards	Awards
				Elite organization

The regression equation for the final *Model 5* takes the following form:

$$\begin{aligned}&\mathit{Logit}\ (\text{winning a Turing Award}) = B_1(\text{publication rate}) + \\ &B_2(\text{max citation}) + B_3(\text{best collaboration variable}) + B_4(\text{early advantage}) + \\ &B_5(\text{visibility in ACM}) + B_6(\text{number of awards}) + B_7(\text{elite organization}) + B_0\end{aligned}$$

where the *dependent variable* is “winning a Turing Award,”
and *independent variables* are

1. Rate of publications prior to the Turing Award
2. Maximum number of citations of a single article prior to the award
3. Best collaboration variable: number of collaborators, coauthors already Turing Award winners, or coauthors members of the Turing Committee.
4. Early career advantage score (a graduate fellowship, publication with the advisor, prestigious first job in an elite computer science institution)
5. Visibility in ACM score (publications, ACM awards, service)
6. Number of honorific awards (awards, NAS/NAE, fellowships) prior to receipt of the Turing Award

7. Employment in top five (elite) computer science institutions

4. Comparative Method of Qualitative Comparison Using the Boolean Approach

The logistic regression analyses were motivated by theoretical models of recognition, but do the models imply that the same combination of factors accounts for a successful outcome of winning a Turing Award for all winners? Andrew Abbott (1992) raised such a concern about regression analysis questioning the assumption that "the causal model is the same for every case" (p. 56). Abbott, as well as Blau and Duncan (1967), admitted that it was not always true. Not all winners follow precisely one success story. Knowing about omitted causes and alternative explanations for winning a Turing Award is important (Cohen et al., 2003, pp. 459-460). Finding combinations of attributes (paths) that describe the minority of cases is the strength of the comparative method of qualitative comparison (QCA).

In the traditional sense, comparative qualitative analysis (QCA) is a case-oriented approach and does not entail the use of variables. Instead, researchers identify "causal" conditions, characteristics, and circumstances describing cases and leading to the outcome. Upon an exhaustive search[90] for "important" conditions, I was able to identify divergences from the academic pattern describing one or two matched cases, which were not helpful in identifying commonalities. Thus, I decided to convert the same variables used for regression into conditions and determine if particular patterns and combinations of educational and career factors are associated with Turing Award winners. The career factors listed in Table 3.3 are theory dependent (see chapter 1) and are "causally" related to the outcome of receiving a Turing Award.

I examined cases for the absence or the presence of six conditions listed in Table 3.3 and coded these conditions as Boolean values (0 or 1) in a truth table. The resulting

[90] I have considered assessing job experiences during graduate school, military affiliations (noted a substantial number among award winners but could not find consistent data for matched scientists), reputational standing as a consultant or advisor, high mobility between jobs or some pattern of employment. These potential variables described one or two cases, but were not sufficient to suggest a pattern.

table was entered into fsQCA software. The fsQCA 2.0 software was generously provided by Charles Ragin on his website.[91] Most frequent combinations of conditions summarized dominant (minority) patterns and were retained for further Boolean analysis. During next steps, set-theoretic minimization rules were applied by the software to determine the most essential conditions describing the cases.[92]

Table 3.3. Factors Relevant to Recognition by Turing Award used in QCA

Condition	*Operational Definition*	*Source of Data*
Condition 1: Early career advantages	A graduate fellowship, employment in one of the top five universities, publications with an advisor (Yes/No).	Biographical record The top five departments were selected based on National Research Council publication (Goldberger, Maher, & Flattau, 1995).
Condition 2: Eminence	The high/low (above/below one) number of honors prior to the Turing Award year (or equivalent years for the control group).	Biographical record
Condition 3: Impact	The high/low (above/below combined group median) number of citations of the most cited publication prior to the Turing Award year (or equivalent years for the control group).	Bibliometric statistics
Condition 4: Institutional Location	Employment (yes/no) in top five research universities for computer science at the time of the award (year).	Biographical record
Condition 5: Collaborators-sponsors	The existence of sponsors among collaborators: co-authors Turing Award winners or members of the Turing Award Committee (Yes/No).	Bibliometric statistics, Archival data
Condition 6: Visibility in ACM	Publications in ACM journals (Yes/No).	Bibliometric statistics

I chose QCA to capture and compare the cases of Turing Award winners holistically, that is, as combinations of career factors. A Boolean approach (dichotomous coding) used by QCA is a "middle road between generality [of variables] and complexity [of descriptive analysis of cases]" (Ragin, 1987, p. 168). QCA requires researchers to identify "causal" conditions (outlined above) related to the outcome that, with the help of

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[91] See http://www.u.arizona.edu/~cragin/fsQCA/software.shtml
[92] For example, conditions that were occurring in some cases but not in others were removed.

Boolean logic and elements of set theory, help to thoroughly compare two groups (in this study of Turing and non-Turing scientists).

The advantage of QCA is that it allows analysis of conditions that are complex, interrelated, or confounded, and thus reflects the qualitative nature of the cases. Variables in the set-theoretical approach, such as QCA, can be represented by adjectives (rich countries, conservative votes), for example, and describe macro-constructs (centralization, erosion of institutions) and complex conditions. The weakness of this approach is that it is oriented toward studying uniqueness, while its strength is in considering and testing alternative arguments or explanations (Ragin, 1987, p.84). Another advantage of QCA is that it allows researchers to examine diverse career narratives (trajectories) and different causal paths that may have been left unexamined by regression analyses. These narratives may not be reflected by current theories and can be used to generate new theories. The combinations of conditions associated with dominant minority of cases might suggest a specific path to receiving recognition, and thus, a new theory of recognition. Therefore, by using a mixed method approach, consisting of the QCA and regression analyses, I was able to complement the findings of each approach, providing greater richness and detail to the understanding of scientific careers. The next three chapters present the findings, based on these methods of analysis.

CHAPTER 4

AWARD-WINNING CONTRIBUTIONS

This chapter focuses on the contributions that were recognized by the Turing Award and the process of identifying the winners. A typical press release for a Turing Award states, "The Association for Computing Machinery has named [a person] the recipient of A. M. Turing Award – its most prestigious award – for his outstanding contributions of a technical nature to the computing community" (ACM, 1974). It is the goal of this chapter to examine what precisely has been recognized—the range and type of contributions as well as the selection criteria and procedures used by the Turing Award Committee. The nomination and selection of the winner entails, to a certain extent, the social construction of achievement and claims of prize worthiness. The question of what constitutes a contribution in computer science worthy of the Turing Award can be answered only if one knows what is defined as "significant," who defines it, and how they define it. Thus, along with the description of the contributions, I shall also examine the evaluation and selection processes used by the Turing Award Committee.[93]

INTRODUCTION

The allocation of professional rewards in science is a significant social process that reflects normative functioning (rules by which scientists organize their community) of a discipline. The process of evaluation for rewards merits attention because rewards contribute to social inequalities and stratification (Cole, 1992). The evaluation system in science has been described as a system of referees consisting of peers acting as status judges. Status judges are "integral" to "any system of social control" as they evaluate the quality of performance for allocating awards or promotions, and maintain standards of performance and "good taste" (Zuckerman & Merton, 1971). However, in evaluations for awards, peers play particularly important roles and the scientists whom they nominate

[93] An inquiry into the values and decision-making of prize committees has been undertaken by scholars studying the Nobel Prize institution (Küppers, Ulitzka, & Weingart, 1982; Crawford, 1984).

and select come to represent computer science to both the scientific community and to the public at large.

Similar to the Royal Society of London, which, in the course of establishing its legitimacy as an authoritative scientific body, developed norms and social arrangements for the authentication of scientific work, the Association for Computing Machinery (ACM) developed mechanisms for the evaluation of quality of publications in its journals and for identifying "long-lasting technical contributions" to computing that are recognized by its most prestigious Turing Award. The Turing Award Committee, which is a subcommittee of the larger Awards Committee, usually consists of five members and is entrusted with the task of reviewing candidates and selecting the winner. A review of contributions for prizes such as the Turing Award differs from a peer review of publications. The most obvious difference is one of time, whereas a publication conveys a recent contribution, the contribution for the Turing Award was often made years ago. Moreover, the work meriting the award is not being presented to the Turing Committee. Instead, Turing Award nominators are asked to state and describe the contribution of an award candidate. Thus, the contribution is not being directly evaluated, as would be the case with publications. Since the contributions of Turing winners are typically made long before the prizes are awarded, the impact of their contributions on the field have withstood a test of time and were memorable and worthy of being nominated for the award. Last, the review of the contributions for the Turing Award is difficult because the identity of the contributors are known (and thus not anonymous) and that carries the weight of eminence (or the lack of it).

The evaluation of scientific quality, which is part of the awards process, is complex and poses two main problems for evaluators in regard to the validity of standards applied and their operationalization (interpretation and measurement) (Sonnert, 1995c). Sonnert (1995c) distinguished two common approaches that scientists use to evaluate their peers: they rely on quantitative indicators (i.e., publications and citation counts) and peer review (a review "in which scientific quality [performance] is judged by other scientists ['peers']", p. 37). Both approaches contain flaws in that quantitative indicators lack validity (i.e., they may not measure what they intend to measure) while peer reviews lack reliability (i.e., peers do not always agree) (Sonnert, 1995c). Evaluations can also be affected by other factors: 1) the absence of clear evaluation standards and selection criteria may leave evaluators to rely on particularistic, functionally irrelevant attributes or preferences (see Long & Fox, 1995); 2) methods of decision-making and the size of the supporting budget could significantly affect the quality of evaluations (Langfeldt, 2001); and 3) committee decisions could be influenced by collective memory, which constructs (or distorts) reputations associated with achievement over time (Lang & Lang, 1988; Olick & Robbins, 1998). Ironically, the tasks that could legitimize recognition by adding validity to evaluation measures and reliability to the peer review process—the operationalization of selection criteria and evidence-based justification for the award—are often neglected by evaluators and hidden from public scrutiny.

In this chapter, I examine award-winning contributions and the methods of evaluation and selection of these contributions used by the Turing Award Committee. The review of internal committee practices is a challenging task because prize committees prefer to keep the evaluation and selection processes secret and surrounded by mystery. One Turing Committee member and former award recipient wrote, "I feel strongly that once the decision is made you want to get rid of the evidence and let the past die" (Hamming, 1973, January 15), thus suggesting that taking responsibility for past decisions is ill-fated. That is, committee members would rather not "have a record of changing criteria" or traces of inconsistencies, providing opportunities for someone to tamper with or question the legitimacy of the award. Even the statutes of the Nobel Foundation, put into effect in 1901, initially did not allow deliberations about the prizes to be open to the public.[94] Their rationale was simple: such secrecy would facilitate the work of the foundation, and "the prestige of the prizes would be more secure if one blocked access to materials that might bring adverse publicity" (Crawford, 1984, p. 84).

[94] §10 of the Statutes of the Nobel Foundation reads, "Against the decision of the adjudicators in making their award no protest can be lodged. If differences of opinion have occurred they shall not appear in the minutes of the proceedings, nor be in any other way made public" (Crawford, 1984, p. 224). Also see Appendix A.

As a result of this decision, the prize committee acquired “self-effacing” characteristics, as described by Burton Feldman, a reality in which decisions seem to come from “some timeless Realm of Objective Judgments” (2000, p. 15). In the opinion of some, this secrecy and invisibility of the “decision-making machinery” only “heighten[ed] the majesty of the prizes” (Feldman, 2000, p. 15).[95]

The demystification of the Nobel Prize began in 1974, when the Nobel Foundation opened its archives (except for the previous 50 years). The access to records led to a number of revelations pertaining to what was considered a “scientific achievement,” “who” was considered to be an important scientist, and the criteria the committee used to recommend scientists. The accessibility and the transparency of the archives of the Association for Computing Machinery (ACM), which awards the Nobel equivalent in computing, promise to have the same demystifying effect.[96] Similar to the Nobel Prize, the opening of the ACM archives to “outsiders” signifies confidence in the transparency and the fairness of the selection process.

The decision-making of any prize committee, including the Turing Award Committee, may involve controversy, debate, and disagreement before the committee reaches a consensus about the final winner of the award. In his essay, “Consensus,” Michael Mulkay (1978/1991) noted that consensus among scientists is both a “social” and “intellectual” process (as perceived by scientists). If individuals accept the existence of an intellectual consensus in science and believe “that consensus about and invariance of scientific knowledge is due to its objective validity,” then they will experience “some difficulty in regarding the content of scientific knowledge as being dependent in any direct way on social processes” (Mulkay, 1991, p. 81). Consensus among scientists is often the outcome of a balance of negotiation, cooperation, collaboration, disagreement, and competition among stakeholders (Mulkay, 1991). Thus, knowing the way scientists

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[95] This holds true in areas outside of science as well, as in the case of the Pulitzer Prize, awarded since 1917. “Although the Pulitzer is prestigious,” writes Leonard Levy, “the public, let alone recipients, knows virtually nothing about how the awards in the ‘Letters’ are decided” (Levy, 1980, p. 1).

[96] Also publications about the work of the ACM Award’s Committee, for example by Gotlieb and Horning (2010), help to bring transparency to the selection process.

arrive at a consensus is important because it points to norms and behavior governing recognition in the scientific community.

QUESTIONS

In a scientific community, compared to other communities, rewards, including prizes, are expected to be relatively "objective," marking the significant contributions. According to the norm of universalism (i.e., "truth-claims, whatever their source, are to be subjected to pre-established impersonal criteria"), originating with Robert Merton (1973), fellow scientists are expected to act as relatively unbiased judges when identifying important contributions (p. 270). How such unbiased judgment is accomplished remains unclear since very little is known about processes for awarding prizes, including who the judges are, how judgments are made, and what bases are used in the decision-making process. Each step of the Turing Award process (i.e., nomination and selection procedures), each actor (i.e., prized scientists, nominators, the committee members), and the characteristics of the contributions may potentially prove to be a critical part of the decision deeming a contribution worthy or not worthy of an award. To understand what makes some contributions worthy of the award, one must learn: 1) What constitutes an award-winning contribution, that is, what are the valued characteristics of award-winning contributions to computing as assessed by the Turing Committee granting the award? 2) How does the ACM decide upon and select a "long-lasting technical contribution" in computing?

Because so little is known about underlying procedures, award selection machinery often resembles a complex "black box,"[97] the inputs of which are the scientific contributions and the output is the winner. Black boxes conceal the social processes that lead to the construction of the prize. In the case of the ACM, the black box contains the Turing Award Committee responsible for the selection of a "significant contribution" that will be recognized as worthy of the Turing Award. In reality, however, each nomination

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[97] "Black box" is a general term in science and engineering that refers to a device whose inputs and outputs are clearly visible but whose internal mechanisms are not.

represents a concerted social effort. A candidate has to be nominated, suggesting that someone has to construct a body of evidence that supports why a person deserves an award, and other computer scientists or professionals have to write letters of recommendation supporting that individual. The task of a nominator (i.e., a "fact-builder") is to build a strong case (e.g., using Latour's term an "alliance") by enlisting strategies that provoke interest and by enlisting human actors-supporters and institutional affiliations that influence the decision-making committee (Latour, 1987). A nomination requires a great deal of coordination and effort by individuals who must evaluate and provide the citation for the award. Thus, the social processes of organizing the nomination and the evaluation, and the transformation of the statements (accounts) of justification into an award citation represent, in part, the social construction of achievement for the Turing Award.

BACKGROUND

Time Profile of Award Recipients

Knowing at what point in their careers scientists received the Turing Award is pertinent to the evaluation of their achievements undertaken by this study. Therefore, I provide information about the age of award recipients as a part of the background for the examination of award-winning contributions that are the focus of this chapter. Based on biographical data, I constructed a time profile describing award recipients (see Table 4.1). Since the award recognizes past accomplishments, the average age of recipients was about 54.5, the youngest being 36 and the oldest 74. The average period from the highest degree earned to the award was about 27.6 years, with several scientists waiting 11 years to be recognized and others, up to 49 years. With regard to the two women in the group, the average was 44.5 years, a much longer period than the average of their male colleagues (27) (see Appendix C).

Table 4.1. Time Profile of Turing Award Winners (1966-2008), N=55

Characteristics of Turing Award Winners	Years
Average age of award recipients	54.5
Age of youngest recipient	36
Age of oldest recipient	74
Average period of time from the highest degree earned to the award	27.6
Average period of time from the highest degree earned to the award among women (N=2)	44.5
Minimum time from the highest degree earned to the award	11
Maximum time from the highest degree earned to the award	49

FINDINGS

I. Contributions

A. Characteristics of Contributions

Types of Contributions

When announcing the award winner, the Turing Committee provides the award citation.[98] In most cases, award citations tend to be general, mentioning a range of contributions as opposed to one specific contribution. Using the techniques of qualitative analysis for the content of the award citations, I coded and categorized the types of contributions in relation to the recognized roles of Turing Award scientists—that is, what they actually did to receive the award. Table 4.2 displays the results and indicates that the committee most often acknowledged theoretical contributions to research frontiers in computing (32.7%), followed by contributions to practice (development, implementation, construction, and one invention) (24.8%), design (e.g., of languages, algorithms, data structures) (17.8%), and contribution in the form of influence/inspiration (16.8%). The acknowledgement of a particular paper or book(s)—a publication of major significance

[98] See Appendix F on the division of intellectual property by the Turing Committee.

that deserved a Turing Award—was identified and mentioned in only eight percent (7.9%) of contributions.

Table 4.2. Types of Contributions Acknowledged in Award Citations (1966-2008), N=101*

Type of Contribution	% of References**
Contributed to theory and research (including the founding of CS branches)	32.7
Developed (built, implemented, constructed, invented technology)	24.8
Designed (specifications, languages, algorithms, data structures)	17.8
Influenced (inspired)	16.8
Authored a specified publication	7.9
Total	100.0

*Note: The base is 101 because I initially identified 101 references to contributions, some of which fell in the same area or subarea upon classification by areas, so the total number of contributions by area and sub-area dropped (from 101) to 56, as seen in Figures 4.1 and 4.2 and Tables 4.3 and 4.4.
** The percentage of references describes the references to particular type of contribution (listed in rows) in award citations.

Subject Areas and Sub-Areas of Contributions

Contributions listed in award citations were also classified according to the subject areas used by the ACM to categorize articles (see Figures 4.1 and 4.2).[99] The first chart (Figure 4.1) summarizes the areas of contribution awarded and reveals that the majority of them fell into the category of Software (about 38%), followed by the Theory of Computation (25%), Computing Methodologies (11%), and the Computer Systems Organization (9%). The least recognized area was Hardware.

[99] The results of the classification were verified (and corrected when necessary) by a senior computer scientist, as described in Chapter 3 (Methods).

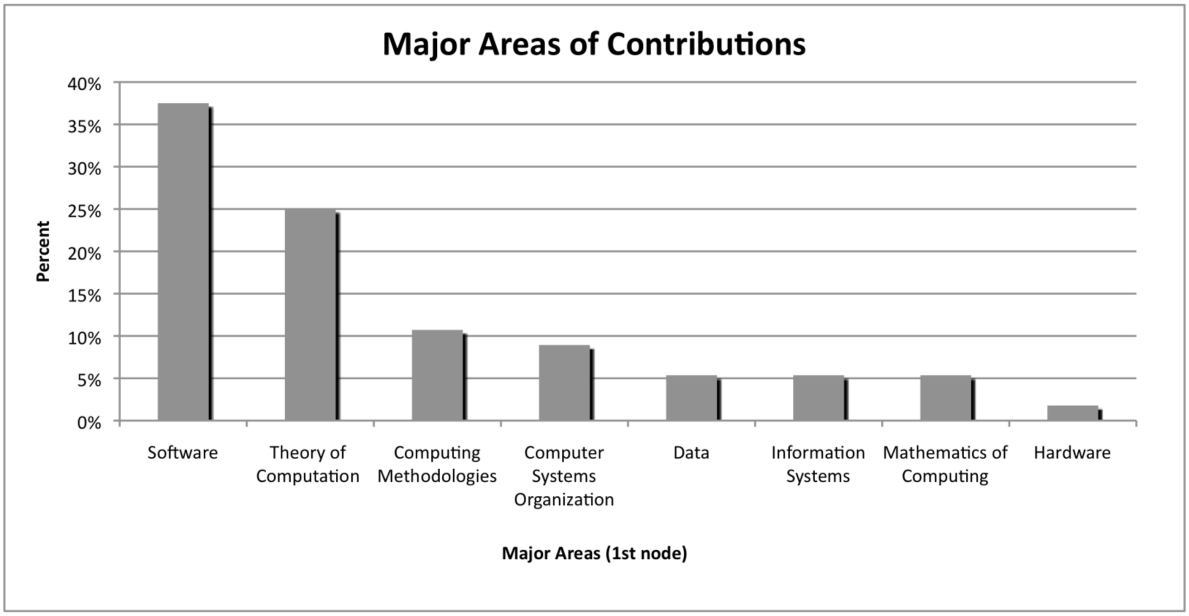

Figure 4.1. Major Areas of Contributions Awarded Over Time (1966-2008), N=56

Figure 4.2 summarizes the sub-areas of contribution and indicates that the predominant sub-areas of awards were Programming Languages (almost 20%) and Analysis of Algorithms and Problem Complexity (13%), followed by Programming

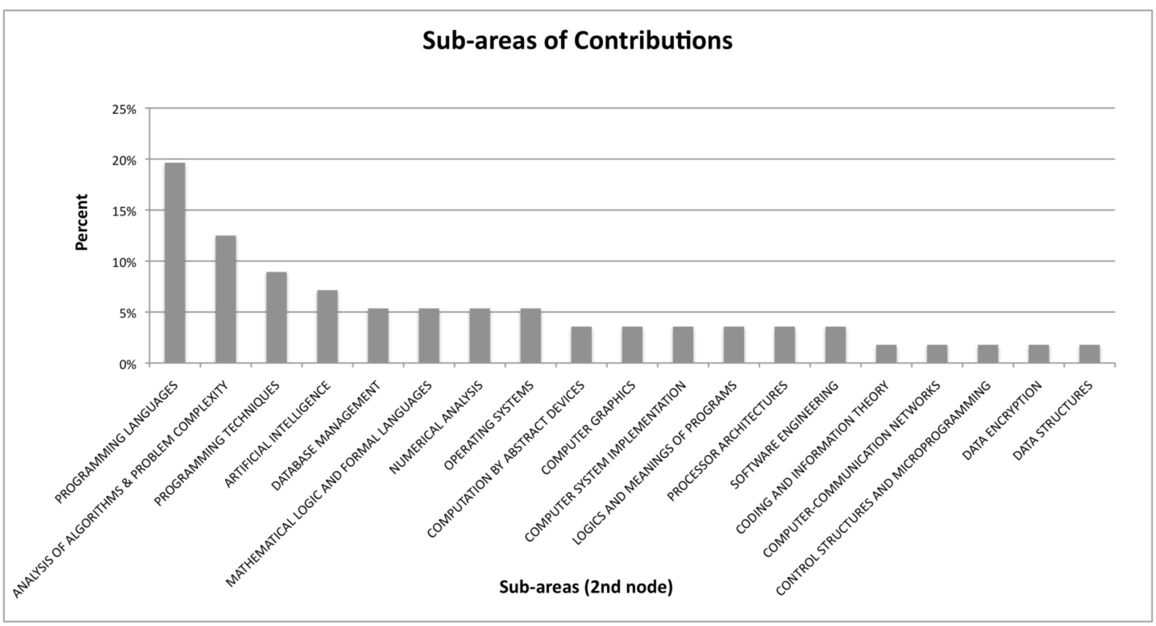

Figure 4.2. Sub-areas of Contributions Awarded Over Time (1966-2008), N=56

Techniques (9%) and Artificial Intelligence (7%). These sub-areas, reflecting core subjects in computing (i.e., languages and programming, algorithms and complexity), are abstract and oriented towards software rather than hardware.

B. Changes in Recognized Contributions Over Time

By constructing Tables 4.3 and 4.4, I intend to compare recognized contributions by area and subareas across decades. Table 4.3 helps to identify patterns of continuity and change over time in the areas of contributions recognized by the award committee. Contributions in the Mathematics of Computing and Hardware were awarded during the early years, in the 1960s and the 1970s. Throughout the 1970s, the 1980s, and the 1990s, the committee recognized a large number of contributions to the Theory of Computation, and from the 1980s to 2008 it recognized a substantial number of contributions in the area of Computer Systems Organization. Awards in the area of Software were more numerous and consistently prominent in all decades, from 1966 to 2008.

Table 4.3. Areas of Awarded Contributions Across Decades (1966-2008), N=56

	Decade (% within decade)				
Area of Contribution	**1966-1969 (n=7)**	**1970-1979 (n=13)**	**1980-1989 (n=12)**	**1990-1999 (n=14)**	**2000-2008 (n=10)**
Software	42.9	38.5	33.3	28.6	50.0
Theory of Computation		30.8	25.0	35.7	20.0
Computing Methodologies	14.3	15.4	8.3	14.3	
Computer Systems Organization			8.3	14.3	20.0
Data	14.3		8.3		10.0
Information Systems		7.7	8.3	7.1	
Mathematics of Computing	14.3	7.7	8.3		
Hardware	14.3				
Total	100	100	100	100	100

Table 4.4 compares contributions by sub-area over nearly five decades. The number of awarded sub-areas reflects the diversity of achievements recognized by the Turing Award. The sub-area of Programming Languages received consistent attention

over the years but more prominently in the 1970s and 1980s (25%-31%), as did the contributions to Analysis of Algorithms and Problem Complexity (15%-25%); contributions to Numerical Analysis were recognized in the decades from the 1960s to the 1980s; and Database Management was recognized during the decades from the 1970s to the 1990s, reflecting the evolution of the knowledge of computing and corresponding technology. Subareas with fewer recognized contributions (Coding and Information Theory, Computer-Communication Networks, Control Structures and Microprogramming, Data Encryption, and Data Structures) produced "one of a kind" major contributions that withstood the test of time. Nevertheless, one may wonder why

Table 4.4. Sub-areas of Awarded Contributions Across Decades (1966-2008), N=56

	Decade (% within decade)				
Sub-area of Contribution	**1966-1969 (n=7)**	**1970-1979 (n=13)**	**1980-1989 (n=12)**	**1990-1999 (n=14)**	**2000-2008 (n=10)**
Programming Languages	14.3	30.8	25.0	7.1	20.0
Analysis of Algorithms and Problem Complexity		15.4	25.0	7.1	10.0
Programming Techniques	14.3	7.7			30.0
Artificial Intelligence	14.3	15.4		7.1	
Database Management		7.7	8.3	7.1	
Mathematical Logic and Formal Languages		7.7		7.1	10.0
Numerical Analysis	14.3	7.7	8.3		
Operating Systems			8.3	14.3	
Computation By Abstract Devices		7.7		7.1	
Computer Graphics			8.3	7.1	
Computer System Implementation				7.1	10.0
Logics and Meanings of Programs				14.3	
Processor Architectures			8.3	7.1	
Software Engineering	14.3			7.1	
Coding and Information Theory	14.3				
Computer-Communication Networks					10.0
Control Structures and Microprogramming	14.3				
Data Encryption					10.0
Data Structures			8.3		
Total	100	100	100	100	100

some sub-areas, particularly of Data Encryption and Computer-Communication Networks that have produced several major developments as early as 1948, have received so little recognition and so late? Was it because they were not “technical” enough or because there were too many people to credit? Interestingly, the recognition of the Internet protocol,[100] representing the sub-area of Computer-Communication Networks, happened after the recognition of the public-key cryptosystem from the sub-area of Data Encryption that ensured the security of data communications over the Internet, possibly because the cryptosystem was perceived as more “technical,” a product of basic science, as opposed to development of the communication protocol. However, once the cryptosystem received an award, it merited the acknowledgement of the communication protocol.

Finding 1 on Characteristics of Contributions and Changes in Recognized Contributions Over Time, (A-B)

Over the years, the Turing Award Committee has recognized a range of contributions from a variety of sub-fields in the newly emerged field of computing (i.e., “breadth” criteria). With respect to the type of contribution, the analysis of award citations revealed that the committee valued contributions to research in computing (32.7% of 101), practice (24.8% of 101), design (17.8% of 101), the influence on the field by inspiration (16.8% of 101), and by particular publication (7.9% of 101; see Table 4.2). The breadth of recognized achievements is reflected in the *subject areas* and the *sub-areas* of contributions. Over the span of 43 years (1966-2008), the major areas of contributions awarded were Software (38% of 56), followed by the Theory of Computation (25% of 56), Computing Methodologies (11% of 56), and the Computer Systems Organization (9% of 56; see Figure 4.1). Within these areas, major sub-areas of contributions awarded were Programming Languages (20% of 56), Algorithms and Problem Complexity (13% of 56), and Programming Techniques (9% of 56; see Figure

[100] The design and implementation of the internet protocol TCP/IP (Transmission Control Protocol/Internet Protocol), developed in the late 1970s and early 1980s, was recognized two decades later (in 2004), after the Internet became an economy of its own.

4.2). With regard to changes in recognized contributions over time, one can observe the evolution from Hardware and Mathematics of Computing of earlier decades (pre-1980s) to Computer System Organization and an even stronger focus on the Theory of Computation and Software during later decades (post 1980s); however, the focus on Computing Methodologies, Theory of Computation, and Software, specifically on sub-areas of Programming Languages and the Analysis of Algorithm and Problem Complexity, have remained consistent throughout nearly five decades.

II. Nominations

Like other prize-giving organizations, the ACM has developed a set of requirements for nominations for the Turing Award.[101] However, during the early years of the award in the late 1960s, the nominations came from members of the Turing Committee, and it was not until the mid-1970s that the nomination procedures underwent significant changes, moving from "internal" to "external" nominations. For the first nine years (prior to 1975), the nominations were primarily internal—only the members of the Turing Committee submitted personal nominations with "supporting evidence." Galler referred to this practice as "inbreeding" and pondered opening the nomination process to all ACM members (Galler, 1971, December 22). The opportunity for change came a few years later, in 1975, when the computer science department at the University of California at Los Angeles asked for nomination forms. The department received a reply from the Turing Award Committee that welcomed suggestions, saying that one simply needed to send "a letter to X with whatever supporting statements or documents" (Galler, 1975, November 4). Furthermore, the letter stated that it "should not be necessary to

[101] The general procedures followed by ACM Award committees state that they publish all the invitations for nominations in the journal *Communications of ACM*, where they note the criteria for the award and list the chair's address, and where nominations should be sent. In addition, they send letters to ACM Key People (a registry maintained by the headquarters of the ACM), soliciting nominations for the Outstanding Contribution and Distinguished Services Awards and to selected computer science chairs, soliciting nominations for the Doctoral Dissertation Award. The general procedures state that "in some committees additional nominations may be suggested by committee members; in others, all nominations must be formally submitted from someone not on the committee" (Ryan, 1989, Sept. 19). Those serving on a committee cannot be nominated for an award, at least not during the time of their service.

make an elaborate case" since "anyone nominated for the Turing Award would be well known to most of us" (Galler, 1975, November 4).

In the next few years (from 1975 onwards), the committee opened the nomination process to members of the computing community, at first distributing the information on awards during the ACM Annual Conference and later in the ACM publication.[102] The time was right because during the five years of service, Turing Committee members realized that they had seen a finite number of nominations. In his third year of serving on the Turing Committee, James Wilkinson admitted that at that stage, he did not have any new nominations. In addition, in 1973, after several years of having been on the Turing Committee, another member admitted that it was difficult "to come up with a [new] list [of nominees]" (Galler, 1972, October 31). Initially, the committee was relatively informal about the information that they wished to collect about nominees—just a letter—but later, they explicitly asked for the submission of a statement with "reasons for nomination" and "people who endorsed this nomination." In an effort to standardize the nomination process, they even created a nomination template. By 1995, the nomination instructions had become more explicit, requesting 1) a curriculum vitae, and 2) "a letter from the principal nominator, which describes the work of the nominee, and draws particular attention to the contribution which is seen as meriting the award," and 3) supporting letters from two other nominators, not co-workers or colleagues but individuals at "more than one organization."[103]

Public nominations presented the committee with a greater number of choices. The nomination letters usually came from colleagues who were in the same academic departments as the candidates or senior industry professionals (e.g., a president, a director, a consultant). In a few notable cases, nominations came from former students,

[102] A printed solicitation for the Turing Award (first) appeared in the *Communications of the ACM* magazine in February of 1977, see ACM. (1977). Awards Committee Solicits Suggestions. *Communications of the ACM*, *20*(2), 121.
[103] The requirements have remained the same for a number of years. See ACM. (2007). ACM A.M. Turing Award Nominations Solicited. *Communications of the ACM*, *50(*3), 14.

a former spouse who herself was an academic,[104] and scientists who would themselves receive a Turing Award a few years later.

Since the criteria for nominations and selection remained vague, principal nominators used various strategies to construct their cases. Often listing multiple contributions, they drew comparisons and similarities to the contributions of Alan Turing and Turing Award winners. They appealed to numbers, authority, and status by soliciting support letters from 19 other supporters or from supporters from nine different countries and from as many former Turing Award winners as possible. When describing a candidate, they often emphasized leadership ("a leader in the development of X"; "played a leading role"; "one of the very few outstanding leaders") and the intellectual prowess of giant proportions ("X is truly one of the field's giants"). The numerous nomination letters illustrate the diversity of forms of values (to what people attribute worth, see Stark, 2009) and justifications used to construct prize-worthy achievements.

In some cases, when candidates were unknown, committee members went to greater lengths to determine who the candidates were. Committee members guarded their personal stamp of approval and respected the opinions of those they trusted:

> When I received the nomination for Q, the name was so unfamiliar to me that I made some local inquiries as to who he might be. I found some surprisingly strong endorsements, from people whose opinions I respect, that he should be considered if ACM is serious about not confining the Award to academic type achievements. Then I happened to hear the candidate give talk myself, and I was impressed with what I heard. I still think that he is relatively unknown, and I very much doubt that any of the others will take his candidacy seriously. (Gotlieb, 1988, May 17)

However, committee members were not always impressed with proposed contributions and, in some cases, were troubled by the lack of worthy candidates (e.g., as it was in 1972, 1975, and 1976). On multiple occasions, someone would suggest not conferring an award during a particular year, stating in one case, "we live in an age of midgets."

Finding 2 on Nominations

[104] This female professor was formerly married to the scientist whom she was nominating.

Over the years, the nomination procedures have undergone profound changes: from internal committee nominations (prior to 1975) with a paragraph of "supporting evidence" to external nominations (from 1975), open to anyone, accompanied by elaborate paperwork. For the last sixteen years (or more), the elaborate paperwork, consisting of curriculum vitae and at least three letters of recommendation, reflected the credentials of nominees and testimonies of their supporters communicating the magnitude of their achievements. While the committee sought "outstanding contributions," nominated contributions were sometimes not particularly substantial, suggesting two challenges facing the committee: 1) identifying major contributions in computing[105] and 2) bestowing the award even when nominations were not strong in a given year (thus possibly accepting contributions of lesser significance than in previous years).

III. Evaluation and Selection Process

The identification of the "winning" contribution starts in nomination letters and continues through the evaluation and final selection of a winner. Letters of nomination build a case by highlighting personal achievements, presenting pieces of evidence, and justifying the claim of worthiness of the contribution for the award. Justifications used in the nomination and selection process in many ways resemble scientific proofs (Boltanski & Thévenot, 1991/2006). An examination of the communicative practices[106] of the

[105] It appears that the committee was looking for "paradigm"-changing achievements but instead received nominations from the area of "normal science" ("research firmly based upon one or more past scientific achievements") (Kuhn, 1962, p. 10). An interesting question to explore in the future is how and when contributions become recognized as being revolutionary and whether prizes can facilitate such recognition.

[106] The communication practices of the committee, having changed significantly over the years, ensure the valued participation of each member of the committee. Prior to 1973, only the chair corresponded with all the members of the committee, which led to grievances from members who felt marginalized and uninformed. In 1973, a new chair, Richard Canning, initiated the mailing of photocopies of all correspondences to all members of the committee to inform them of how other committee members had voted. As a result, the committee moved away from the strong leadership of a chair to a more democratic selection process in a "committee-like" way. In the following years, a new chair suggested yet another model, requesting that committee members send any correspondence they wrote to all the other members. As a result, committee members remained happy and involved. These examples illustrate that the form of communication itself constitutes a method of selection of future winners. In addition to communication practices, the rule that within a five-year period of service, one committee member would become the chair during the fourth year allowed the committee to operate as a "committee of equals" (Williams, 2007). The rotation of these positions helped to avert power struggles within the committee.

committee could provide insights into how the worth of the candidates has been constructed or influenced. Below are three excerpts[107] of deliberations of committee members that reveal the way information about a candidate formed a positive or negative impression on a committee member and how the information was later shared with other members.

Example 1. The claim is made that person X is outstanding, as evidenced by the fact that he has been "an invited speaker at both IFIP and the International Congress of Mathematicians" (Wilkinson, 1972b). Alternatively, person Y might have produced a negative impression, as evidenced in the following quote: "Y's recent talk was so strange as to make me wish to avoid another one like it and then find it necessary to publish in the Journal" (Hamming, 1975, April 15).

Example 2. Some nominees were noted to be "intellectual giants with established reputations in other fields" (Knuth, 1976, May 7) as opposed to person Y, who was "no intellectual giant although he was a friendly and competent manager" (Knuth, 1975, April 8).

Example 3. The argument was made that the "quality of the literature in any field is of immense importance to its development and X might well be given the award for his contribution in this area alone." As a result, "In the process of updating my biography of the work of X, my opinion of him rose even higher that it was before. …In striking contrast to my experience with X, I found my attempts to update [Y'] biography affected my opinion of him adversely" (Wilkinson, 1973, January 26).

These examples of reputation building demonstrate how prior eminence, intellectual prowess, and publications created a positive impression while "strange" talks, lack of intellectual prowess, and a meager publication record created negative impressions.

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[107] I selected these cases to illustrate how committee members evaluate candidates. However, these cases do not necessarily represent all the deliberations of the committee. The rationale for their selection and inclusion was that they represented actual deliberations and evaluations of candidates—a rare type of evidence of the judgments used by committee members.

A. Valued Criteria Over Time

1. Impact: pragmatic/usability versus theoretical/depth

Archival evidence suggests that when selecting a winner, the committee has taken the breadth of contributions into account. In other words, the general consensus has been that the award should not be limited to a particular area, but rather, it should "recognize leadership and contribution in a variety of areas" (Galler, 1971, December 22).[108] However, Tables 4.2 and 4.4 show that some areas (software) and sub-areas (programming languages, algorithms, and problem complexity) have received prominent attention throughout the decades while others have received little recognition. The omission of some topics over the years has prompted the committee to recognize these topics in later years. For example, by 1976, ten years after the creation of the award, the committee had not recognized any contributions to the theory of computing (not counting Alan Turing himself), which provided a strong argument for selecting a contribution in the theory of computing that particular year. On the other hand, the committee had acknowledged giving too much credit to contributions in the subfield of artificial intelligence (AI) (Knuth, 1975, April 8).

Archival documents provided evidence that the Turing Committee struggled to find workable criteria for evaluation in conferring awards and had to address a clash between academic and industry values. As early as 1972, six years after the first award, the Turing Committee had to address the meaning of "technical" as a criterion of the award having been accused of "discrimination" against potential "award winners whose background and contributions [lay] principally in the area of commercial interest" (Alt, 1972, August 19). The chair of the Awards Committee, Franz Alt, admitted that the working definition of the award was ambiguous and that the composition of the Turing Award Committee was not sufficiently broad. Furthermore, out of the five voting

[108] It was also a recommendation of ACM officers that technical contributions "should not be limited to fields circumscribed by computer science (whatever that is), since such limitation may perpetrate a precedent the Association could later regret" (Alt, 1972, August 19).

members of the Turing committee, often only one or two were industry professionals. Even academic members of the committee agreed that the commercial world was receiving "scant recognition" (Wilkinson, 1972, October 13). Although a decision was made not to discriminate against candidates with commercial interests, finding an outstanding candidate from industry was difficult. It was even more difficult to present a case to the committee of a "gifted problem solver" from industry (Wilkinson, 1972, October 13). As a possible solution to discrimination against industry professionals, a suggestion was made to try harder and make a "well-reasoned case" for industry candidates (Wilkinson, 1972, October 13).

Some committee members thought that the exclusion of industry candidates was partly due to the definition of the Turing Award. They argued that the unofficial definition, reflecting the perception of the award by most ACM members, was the award was given for the "contribution in the field of computer and engineering," which was broad and inclusive. In 1972, Franz Alt, on behalf of an ad hoc committee, proceeded to clarify the qualifications of a contribution of Turing caliber as well as the definition of "technical" as a criterion of the award, enumerating that a Turing contribution

(1) should have high intellectual content;

(2) should have had <u>significant influence</u> on a major segment of the computer field;

(3) may possibly reflect a lifetime of contribution, as opposed to a single activity, which may be difficult to measure; and

(4) may possibly be attributed to more than one individual, in which case the awarding of the prize jointly to several individuals should not be overruled. (underlined in the original; Alt, 1972, Aug. 19)

While widening the spectrum of possibilities, these guidelines were insufficient, for the committee continued the battle of standards. Assuming the responsibilities of a chair of the Turing Award Committee and being an industry professional, Richard Canning was "distressed" that so many award winners were "literally unknown to the bulk of the people in the computing field" (Canning, 1972, September 23) and suggested that "not only the quality of work, but also the widespread impact of that work, should be honored." Along with desires of others to give more weight to the commercial sector, he was determined to "select someone whose work is recognized as important by a goodly number of people in the commercial environment" (Canning, 1972, September 23). In the following year, 1973, he attempted to introduce his measure of significance of contributions. Committee members nominating new candidates were asked to state their "opinions" about the "breadth of the influence" of a candidate's contribution, specifically "What segment or segments of the computer field are actually using his contributions? How frequently are they used—occasionally? regularly? daily?" (Canning, 1973, January 9). Usability of a contribution, empowered by high number of users, implied that the contribution was known in the computing community, and thus, if selected, would be widely respected.

The reduction of the criteria of "influence" to "usability" did not satisfy the academic members of the committee, in particular, Bernard Galler. Galler suggested that the committee "also try to recognize the depth of the conceptual contribution just as much" (1973, January 16), keenly asking, "How long would it take to get Einstein's Theory of Relativity to be appreciated if one looked at [its] frequency of use?" (Galler, 1973, January 16). Canning held his ground, replying, "I am not going to hold my breath until such a person [as Einstein] shows up [in the computer field]." He added that he had "a deep faith in the intelligence of the 'masses,' particularly in the computer field" because they "sense a level of elegance that we as individuals are likely to miss." As an example, he argued that FORTRAN was not an elegant language, but it had "the elegance of utility," and he clarified his point that he would favor "widespread use" over "elegance" (Canning, 1973, February 11). Galler disputed the reasons for the success of FORTRAN, noting that they had "nothing to do with elegance of utility or any other kind." According to Galler, the success of FORTRAN stemmed from its being "the first higher-level language with a translator that worked and was efficient" and second, because IBM backed it, indicating a "big investment in user programs and training" (1973, January 16). Galler's point was that an important contribution may not enjoy "immediate marketable visibility" or "widespread use," so it was the task of the Turing Committee to recognize such cases. In his closing remarks, just as he was to relinquish his seat as chair of the Turing Award Committee, Canning emphasized that it was very important to him that "the person's work have significantly influenced actual behavior in the field," by which he meant that the work "is in fact being widely used" (Canning, 1973, February 11).[109] These arguments about the criteria of "usability" versus "depth" reveal a tension between the "pragmatic" and the "theoretical" values of the Turing Committee members, some of whom were practitioners and others were academicians.[110] The composition of the committee to a certain extent mirrored the polarity of computer science, alternately constructed as both a science and a technology.

Despite their lack of consensus, the ad hoc committee, headed by Franz Alt in 1972, seemingly resolved the issue of ambiguity, and the Turing committee established a set of possible (but not exhaustive) criteria for contributions. These guidelines specified a range of acceptable contributions and defined the meaning of "technical," but they did not put to rest the issue of ambiguity of the criteria for the award. In subsequent years, the criteria for contributions were questioned again because of the committee's inability to identify candidates from industry. Upon assuming his role of the Turing Award chair, Galler stated that he would treat such matters as he would a doctoral thesis, saying, "I know a winner when I see one, but it's hard to tell you the criteria in advance" (Galler, 1974, January 21). From a conversation with Lou Stevens of IBM, one committee member learned that even IBM had very few people "who had extensive influence across the field while working for a company" (Carlson, 1975, May 29). One explanation for the scarcity of industry candidates could be that, compared to academia, they experience more challenges distinguishing themselves as individuals and owning their intellectual property. Their projects are often collaborative and their intellectual property often belongs to a company.

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[109] A similar example is Bachman's voting against Codd because relational databases were not commercially successful, see the interview with Bachman by Thomas Haigh (2006). "Charles W. Bachman Interview: September 25-26, 2004; Tucson, Arizona." *ACM Oral History Interviews*.

[110] The theme of usability was just as prominent in nomination letters. Some engineers placed value on designing a product that "opens computing to millions of people." One committee member remarked that individuals X and Y are "wide-ranging individuals of solid intellectual credentials, who turned their talents to a practical need when they recognized it" (McCracken, 1984, March 24). Furthermore, the same nominator attributed practicality to Alan Turing himself, stating that "Turing's practical side is not currently part of the folklore, of course, but perhaps Hodges' biography will help the computing world realize that he was an intensely practical man when the occasion demanded, as well as an intellectual giant" (McCracken, 1984, March 24).

2. Timing

The organizational rule of bestowing only one Turing Award per year translates into not being able to either withhold the award in the absence of a worthy candidate or being able to bestow more than one award to deserving candidates in a given year. A strong list of nominees challenges the committee's decision-making and sometimes the age of candidates figures into their decision. For example, it was once argued that candidate X dominated "not for reasons of excellence so much as the matter of timing" (Steele, 1990, July 24). Because candidate X was senior to the other candidates by a substantial number of years, the case was made that person X was "deserving" of the award, particularly in light of someone younger having already been recognized for contributions in that area. Such a case was unusual considering that awarding younger candidates was more difficult. One of the chairs of the Turing Award Committee, Kelly Gotlieb, admitted that the age of committee members restricted who they knew and thus disadvantaged the younger cohorts of contributors (Williams, 2007).

3. Prior and Multiple Awards

In one year, 1970, Jim Wilkinson received not only the Turing Award but also the Von Neumann Award, awarded by the IEEE Computer Society. After joining the Turing Award Committee, he raised the question of whether he would have been awarded the Turing Award if the committee had known of the other award. His remark forced the committee to re-evaluate its decision-making process and consult with other organizations such as the International Federation of Information Processing Societies (IFIPS) and the IEEE Computer Society to preclude the granting of multiple awards to the same person in a given year.

As the Turing Committee became sensitive to the issue of prior awards, for a number of years it tried to penalize overly recognized candidates (those who had prior awards) by subtracting a few points from their evaluations. This measure came from Bernard Galler, who strongly supported not bestowing an award on an individual who had already received other awards. Being part of the Turing Committee in 1974, Wilkinson admitted that Galler's suggestion was "by no means easy to follow," for a large percentage of candidates had received a number of awards.   The penalizing measure, proposed in 1972, had another unfortunate outcome—it disadvantaged Grace Hopper who, as a woman pioneer, had already won several other awards and was nominated for the Turing Award.[111]

B. Selection Process Over Time

The official selection procedures were originally established and recorded in August 1969 by Bill Lyons when he was a chair of the Awards Committee. Lyons proposed that the Turing Award Committee consist of five voting members (with a new one appointed each year by the president of the ACM; and ex-officio chair of the Turing Committee becoming the chair of the Awards Committee). If a committee were not able to meet, the election would take place by mail, each voting member providing the names of three to five nominees (and justifications, or so-called "cited contributions") to the chair, who in turn, would select "three to five frequently mentioned" candidates in these lists and send them back to the voting committee. After the committee members ranked the candidates, the chair would prepare a consolidated ranking. The final approval was left to the president of the ACM and the executive committee, who simply accepted a new winner.

Over the years, in addition to holding meetings and discussions (if they did take place[112]), the committee's evaluation and selection procedures also involved various means of ranking the candidates. In the 1972 ranking, committee members rated candidates according to the following categories:

(1) Outstanding – no question that he should get the award sooner or later against almost any competition;
(2) Plausible, but not a true great;
(3) Does not deserve the award (Placement in this category will probably indicate the judgment that the

[111] Grace Hopper was nominated for the Turing Award by the first ACM female president, Jean Sammet. Hopper's candidacy was carried forth in 1972 and voted upon again in 1974, but the committee was less favorable to her candidacy at that time.
[112] Gotlieb and Horning (2010) report that the Turing Committee meets in-person annually but archival documents indicate that there were exceptions.

contribution is too narrow);

(4) I am not sufficiently familiar to judge, but see his stated contribution as one that could be worthy;

(5) Not familiar, but don't think the stated contribution could measure up. (McIlroy, 1972, Jan. 25)

In 1973, committee members ranked the candidates by assigning numbers rather than categories (1=most desirable candidate). In the second round, when the list had become narrower, the chair asked committee members to write a page describing the contribution(s) "that the man has made" ("one or two contributions or a lifetime of contributions") and the breadth of influence of the contribution.

In 1975, when Bernard Galler became chair, he modified the voting system. Members were asked to assign a number from 1 to 18 (the number of candidates, 1-top choice) to each candidate and allowed each committee member to submit six 6's or 1's or any other combination. The votes were then added and averaged, and the weakest candidates were dropped while the rest continued to the second round until a winner had emerged with the lowest number of marks. However, the selection rules varied for other years and other committee members. The voting instructions in 1988, for example, asked members to cast 20 votes for 9 nominees in any combination. The voting from 1990 onward introduced the practice of pseudo-votes for the initial straw poll conducted prior to voting. Thus, throughout most of its history, the Turing Committee has relied on preferential ranking[113] as a way of conveying the strength of member's convictions, values, and merit of candidates. Such personal judgments have been transformed into numbers, compiled and averaged. Since ranking rules have always been informal, committee members have been able to exercise a great degree of latitude. In one particular case, for example, a number of committee members ranked their top choices, leaving many candidates unranked, possibly because they did not regard them as prize-worthy or because they were not familiar with them. As a result, the marks of unrated candidates "defaulted" to the lowest score. We may conclude that the marks did not necessarily reflect the merits of candidates but instead the weights of the "opinions" of

[113] This is a system of ranking of candidates from best to worst. As such, preferentiality is the criterion.

worthiness of committee members. The final markings were an average of the individual non-standardized judgments of the committee members.

Finding 3 on Evaluation and Selection Process, Valued Criteria and Changes Over Time (A-B)

The Turing Committee developed internal institutional decision-making procedures to facilitate the selection of Turing Award winners, which provided some consistency over the years with regard to the size of the committee, their roles, and the general process of the decision-making. The procedures did not, however, specify the basis on which the selection should be made, nor did any evidence reveal any comprehensive assessment of the candidates. In their discussions, committee members tended to assess candidates' worth based on their prior eminence, intellectual prowess, and publications that created a positive impression of a candidate. The available evidence also revealed that the committee used a multi-stage ranking system to determine the winner. Even then, the ranking procedures varied from year to year and from one committee to another. By comparison, Nobel Prize committees in chemistry and physics often arrived at a consensus without voting (Crawford, 1984). With regard to valued criteria used by the Turing Committee over time, the focus on the impact of contributions remained consistent, revealing two seemingly irreconcilable standards applied to contributions: pragmatic (embraced by industry and measured by "usability") and theoretical (embraced by academia and measured by "depth"). However, the priorities of the committee varied as a result of weighing the impact of contributions, area of contribution, timing and the age of the contributor, and sometimes the number of prior awards.

CONCLUSION

In the beginning of this chapter, I posed the question of what constituted a Turing Award contribution. Specifically, I asked what were the valued characteristics of a contribution? The analysis of award citations revealed that over 60 percent of contributions primarily fell into two areas, Software (38%) and Theory of Computation (25%), indicating the focus on practice and theory and creating a niche for computing between hardware (not including it) and mathematics (including it). The recognized (and thus valued) contributions, representing award-winning work, encompassed: 1) theory and research (new results, new disciplinary branches) (32.7%), 2) practice (developed, built, implemented, invented) (24.8%), 3) design (specifications, algorithms, languages or data structures) (17.8%); 4) influences by inspiring others in the field (16.8%), and 5) authoring a specific publication (7.9%). Although theory and research, which are more closely associated with science, constitute a single dominant category (32.7%), the contributions to practice and design together (42.6%) represent the realm of technology (art and craft) and are just as prevalent among Turing Award contributions.

The analysis of committee deliberations provided insights into what the committee valued over the years. Historically, the Turing Award Committee has made an effort to recognize contributions from a variety of sub-fields (i.e., the "breath" criteria; other criteria were age, area of contribution, and prior awards). However, a conflict emerged between the two valued standards applied in the evaluation of contributions: the pragmatic (embraced by industry and measured by "usability") and the theoretical (embraced by academia and measured by "depth"). Thus, the findings indicated that in the heterogeneous field of computing the application of consistent standards was often problematic. The lack of criteria corresponding to particular categories of achievement, accounting for the diversity of contributions in computing, left significant freedom to the committee members to decide how to evaluate award candidates.

In the process of analysis of award citations, I found that many citations did not clearly indicate what exactly constituted "the unit of contribution." Although the committee asked nominators to specify a particular contribution deserving an award, committee members were open to recognizing life-long achievements as well. This observation was particularly discomforting because in science "the unit of scientific achievement is the solved problem" (Kuhn, 1970, p. 169). In computing, it was not clear what problems the recognized contributions solved. However, a solution to a "problem" in computing may include designing or engineering an artifact, algorithm, or a language, which, in itself, was a tangible and useful contribution (it could create a "paradigm" for the work of others).[114]

The second question of this chapter was how did the ACM decide and select a "long-lasting technical contribution"? The five voting members of the Turing Committee typically consisted of men[115] from academia and one or more from industry and in some cases of previous Turing Award winners.[116] Archival data provided evidence that the Turing Committee had institutionalized decision-making procedures, but it had not institutionalized the criteria for evaluating Turing Award contributions or the selection rules. Furthermore, as it is the case with less-developed scientific paradigms, consensus was difficult to achieve in the emerging field of computing. Judgments about the credibility and the prize-worthiness of candidates for the award were left to the personal judgment of each committee member. The committee, satisfying their scientific/moral sense of fairness, reached consensus by mathematical means, averaging the preferential rankings of its members.[117]

A conclusion emerges that within the Turing Award Committee, seemingly committed to universalistic standards of merit in judging contributions, the inherent

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[114] The types of contributions recognized by the Turing Award (research/theory, practice, design, and influence) contrasted significantly with categories of discoveries, inventions and improvements, recognized by the Nobel Prize, overlapping perhaps in the area of invention (although only one Turing Award citation used the word "invention"). Award citations for the Turing Award did not use the word "invention," as if it would undermine the merit or the scientific nature of the contribution (yet scientific inventions are rewarded by Nobel Prizes).

[115] I found that women were part of the Turing Committee in the late 1990s and after 2000, which may have contributed to the selection of women as Turing Award winners in 2006 and 2008.

[116] It was clear to some members of the Turing Committee that the committee was lacking epistemological diversity, which is important, for it "supports the existence of various types of excellence" (Lamont, 2009, p. 10).

[117] In his careful study of the theory of committees and elections, economist Duncan Black characterized the process of identifying the most legitimate and suitable method of election as a jump over the "unbridgeable chasm between the universe of science and that of morals" (1998, p. 69). In 1785, Condorcet, a French philosopher-mathematician and political scientist, proposed that the most moral and fair method would be to pick a candidate "who stands highest on the average on the electors' schedules of preferences" (Black, 1998, p. 70). This criterion, Black argued, appeals to "our sense of justice" via "mathematical symmetry" (Black, 1998, p. 72). Even then, committees needed to make a choice among at least three types of averaging methods. Black argued that since it was impossible to prove that any one mean was a superior measure of average, no one candidate was necessarily the "best."

ambiguity of standards and the quality of information about nominees and their contributions produced conditions that supported potentially particularistic standards in the allocations of rewards (Long & Fox, 1995). With vaguely specified criteria for the selection of winners, committee members had to largely rely on their personal assessments of candidates' worthiness. Whether they did so intentionally or not, committee members had the power to exercise their own preferences (quality standards, tastes, attention to functionally relevant or irrelevant attributes of candidates). Lesser-known candidates (women, industrial scientists, non-U.S. scientists) were likely to have been disadvantaged by such process because they and their work would be less-known by the committee and they were likely to have fewer allies to support their nominations. Historical evidence, exemplified by the recollections of Charles Bachman, the Turing Award winner in 1973, conveys the importance of personal knowledge of a candidate and possible sponsorship:

> Dick Canning was the key point man in my being awarded the ACM A. M. Turing Award. Though other people obviously helped in those things, you get a feeling that someone was the driving force behind it. In these affairs, you need a strong, well-liked sponsor. (Haigh, 2006, "Charles W. Bachman interview," p. 99)

His comment suggests that Dick Canning might have acted as a "reputational entrepreneur" influencing the (favorable) presentation of Bachman to the committee (Allen & Parsons, 2006, p. 813).

The review of the selection process for the Turing Award revealed a strong focus in all stages of the process—from the nomination to award citation—on the contributor rather than on the contribution. Although prior eminence, intellectual prowess, or publication record were not the explicit evaluation criteria of award candidates, the available evidence indicates that these indicators were used in deliberations by some members, and these criteria impacted their perceptions of candidate's prize-worthiness. The requested materials—a curriculum vitae, a letter of nomination and other letters of support—presented a variety of information about a candidate that, depending on the value attached by an evaluator, could support or discredit the candidate. In addition, the available nomination letters indicated that nominators commonly did not limit themselves to describing and assessing only the merits of contributions—they also assessed contributors. The tendency to evaluate contributors together with their contributions was also observed in communications among the Turing Committee members found in archival documents. Because the judgments of contributions could not be separated from the judgments of contributors (confirming findings by Latour & Woolgar, 1986, p. 202), the evaluation of scientists for the Turing Award resulted in an overlooked practice of judging both the merits of contributions and contributors. The confluence of these two actions, or more precisely, the indivisibility of evaluations of contributions from the evaluation of contributors in the review process, created a tension to satisfy both choices, that is, to select an important contribution and a contributor worthy of an award. This may explain why award citations often focused strongly on award winners rather than on the profound impact of their contributions.[118]

The prize-awarding activities of the ACM have shaped and will continue to shape what is valued in computing. However, the ambiguity in the award-selection machinery still casts doubt on what exactly is being rewarded and how the decision is made. Describing the creation of a Nobel Prize winner, Crawford (1998) aptly captures the magic of the process: "He (rarely she) springs from anonymity into stardom through a decision seemingly handed down from above, untouched by human hands" (p. 1256).

This chapter's findings contribute to the understanding of the evaluation of award winners in two ways. First, a peer review does not by itself guarantee "fair" and "unbiased" judgments. Compositional homogeneity of the selection committee, ambiguous criteria of evaluation, and informal ranking procedures, observed in archival documents and reported in this chapter, appear to reflect the values (e.g., prize-

[118] For example, award citations that focus on award winners state "For pioneering work on internetworking, including the design and implementation of the Internet's basic communications protocols, TCP/IP, and for inspired leadership in networking" or "For his fundamental contributions to numerical analysis. One of the foremost experts on floating-point computations, Kahan has dedicated himself to 'making the world safe for numerical computations.'" (appealing to the greatness of the person); while the few citations that focus on contributions state "In recognition of their seminal paper which established the foundations for the field of computational complexity theory" or "For pioneering contributions to the theory and practice of optimizing compiler techniques that laid the foundation for modern optimizing compilers and automatic parallel execution" (appealing to the greatness of contributions).

worthiness, significance of research, possibly resulting from "cognitive particularism," see Travis & Collins, 1991) and wide discretion of the committee members in selecting Turing Award winners.[119] The use of functionally irrelevant characteristics is particularly likely to occur in the 1) absence of functionally relevant criteria, or 2) when there is a limited agreement on relevant criteria for judgment, or 3) when criteria are ambiguous (Cole, 1979; Long & Fox, 1995, p. 63). Second, public claims of prize-worthiness require justification, but award citations and archival materials attest to limited attempt to provide evidence and to justify in what ways a particular contribution was significant or had a substantial impact. An award such as the Turing Award merits a clear and comprehensive method for determining the rules of eligibility as well as the criteria and procedures for selection and evaluation of winners. In the absence of such a method and clear criteria, contributions will remain subject to the authority and the (unjustified) personal preferences of the decision-makers.

In the next two chapters, chapter 5 and 6, I investigate the education and career achievements of Turing Award winners and identify the factors associated with winners that differentiate them from non-winners. In addition, in chapter 6, I compare the contribution of these factors to the likelihood of being a Turing Award winner. If the contributions of Turing Award winners were truly outstanding, it is reasonable to expect that the data collected contain evidence of superior productivity of winners or a higher rate of citations than that of the control group. This expectation is supported by the criteria used in the award deliberations discussed in this chapter (i.e., significance of a contribution, prior eminence, intellectual prowess, and publication record). In the final chapter, chapter 7, I will compare these criteria with the factors most strongly associated with Turing Award winners (i.e., recognition).

[119] If the committee were to become more diverse, having agreed upon procedures and criteria would become an even greater necessity.

CHAPTER 5

EDUCATIONAL ATTAINMENTS OF THE AWARDEES

This chapter examines the pathways of Turing Award scientists beginning with their higher education— (terminal) bachelor's, master's or doctorate training—in relation to the second question of this study concerning education: which educational factors are associated with and differentiate the winners of the Turing Award from the control group of non-winning computer scientists? As consistently reported in various sources, the professional identity of scientists begins with university training—the earliest part of their professional public record. Beginning the comparison of scientists with higher education is a strategic choice. Higher education confers entrance into many valued occupations, particularly in science and engineering, and provides "increased chances for income, power, and prestige on people who are fortunate enough to obtain it" (Sewell, 1971, p. 793). In particular, the undergraduate level was noted to be one of the "latest points" of "standard" entry into science and engineering fields (Xie & Shauman, 2003, p. 96). Since academic credentials and advanced degrees (in particular, Ph.D.) are often the minimum requirement for a permanent research position in these fields, higher education represents a strategic starting point from which *research* careers in science and technology are launched.

INTRODUCTION

The organization of the American system of graduate education can be described by four key elements: "(1) a decentralized system of colleges and universities; (2) competition in a widening market of students, faculty, and financial resources; (3) institutional pluralism (a strong private sector competing with diverse state systems); and (4) federal funding characterized by multiple agency sponsorship and peer review competition" (Graham & Diamond, 1997, p. 200). Autonomous institutions, and within them, departments—grouped by discipline—recruit, train, and certify graduate students. American doctoral programs generally include a few years of coursework, final examinations (sometimes supplemented with a language requirement), a number of years of research, and a dissertation (Walters, 1965). Over time, graduate education in science and engineering has moved more and more toward faculty-student collaboration in which graduate students "work on faculty's funded research projects (as opposed to working elsewhere), acquire skills and experience, and proceed toward a doctoral degree" (Fox, 2000, p. 57). Connections with faculty are highly consequential for students, who in the process of their training, acquire not only skills and knowledge but also values, norms, and beliefs (Zuckerman, 1977) through what the faculty "convey, demonstrate, and exemplify" (Fox, 2003, p. 91). This model of graduate education and research funding supports universities and, as a result, university administrations are unlikely to interfere in the decentralized arrangements of advisor-advisee relationships (Fox, 1998, 2000).

In chapter 1, I hypothesized that Turing Award scientists, unlike the control group, began their careers with small advantages such as a fellowship, a publication with their advisors, or an initial job in the top five university programs in computer science.[120] The first, fellowships, are highly regarded by scientists who often list them as awards on their vitas. Fellowships provide not only a means of support and a motivation to devote oneself to one's studies but also a boost to self-confidence, as reported by scientists (Sonnert & Holton, 1995a). Second, publishing with an advisor is a pivotal experience that positively affects a student's subsequent productivity (Long & McGinnis, 1985) and later career placement (Fox, 2003; Crane, 1965; Zuckerman, 1967). Third, initial job placement in top computer science departments provides an important career advantage since later productivity conforms to departmental norms and expectations (Allison & Long, 1990; Long, 1978; Long & McGinnis, 1981) regardless of the basis for recruitment. Small differences between Turing Award winners and the control group in the beginning of their professional careers could become cumulative (see Allison, Long, & Krauze, 1982; Cole & Cole, 1973; Merton 1942/1973; Zuckerman, 1977) and prove to be crucial (leading to publications and awards) for the professional success that culminates into being honored with a Turing Award.

[120] First jobs in industry were not counted toward "top five programs." Only academic institutions were counted.

I expect that early differences between Turing and non-Turing scientists in connection to their research, resources, and job prospects start to emerge during their graduate training. Those differences are part of the larger process of stratification that occurs partly because the rewards system in science operates with "differential effectiveness" (Zuckerman, 1977, p. 189) in spotting potential talent and providing early resources only to some scientists.

A part of this chapter addresses the educational background of all Turing Award scientists (N=55) and the rest compares American Turing Award winners (N=30) to the control group of non-winners (N=30) and their (common) advisors (N=30). In particular, I provide information about home countries of Turing Award winners (N=55), academic institutions attended, degrees over time, types of degrees over time, and fields of study, both overall and over time. The comparison of Turing Award and control group scientists (non-winners) that follows includes only American academic and semi-academic[121] scientists and their advisors. The matching of Turing and control group scientists was designed so that both scientists attended the same institution and were trained by the same advisor. This was done to minimize the influences of differences in prestige and quality of training among winners and non-winners when analyzing their career achievements (see chapter 3). In this chapter, I examine graduate training and assess Turing compared to control group scientists in terms of 1) early career advantages, 2) productivity and impact measures compared to those of their (common) advisors, and 3) productivity and impact measures of those advisors who published with their Turing Award and control group students during graduate years (or up to 2 years after the graduation year).

FINDINGS

Countries

[121] Turing Award scientists with mixed backgrounds are those who worked both in academia and in industry. Very few scientists worked only in academia.

Over the years, the Turing Award has demonstrated an international reach by recognizing researchers from both the United States and other countries. However, since the Association for Computing Machinery is primarily a U.S. organization, it is not surprising that about 75 percent of all award winners from 1966 to 2008 are closely affiliated with the United States (see Table 5.1). Among them, the majority (85%) were born and educated in the United States and at the time of the Turing Award either worked in the U.S. (80%) or in other countries (5%). The other 15 percent of scientists were born abroad (e.g., in Canada, China, India, Latvia, UK, Venezuela) but were educated and had successful careers in the U.S. and thus were counted as American (see Table 5.1).

Turing Award recipients from outside of the United States (25%) ("foreign scientists"), in most cases, are nationals of the countries where they were born, educated, and employed (see Table 5.1). However, on an individual level, life stories are often more complex as seen in their mobility patterns. Two foreign scientists pursued graduate education in the United States. Some foreign scientists worked in the United States or other countries at some point of their careers and in most cases returned to their home countries or found a new home (e.g., Israel). To summarize, countries with the most winners from outside of the United States are the United Kingdom (4), Israel (3), and Norway (2). These countries together with Denmark, the Netherlands, Canada, and the United States can be said to form a trans-Atlantic (English-speaking) "world" of computer science, an information network of scientists and their research.[122]

The control group of scientists (N=30) resembles the group of American Turing Award winners in their (country of) origin and education. Among the control group, 80 percent were born in the United States and 20 percent were born abroad but were educated and worked in the U.S. Only 6.7 percent of those born abroad returned to their countries of origin. The countries of birth (Switzerland [n=1], Israel [n=1], Denmark

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[122] Archival and secondary literature confirmed that these scientists were mobile, visited foreign universities, joined the same scientific societies, attended conferences, and many had common research interests.

Table 5.1. Turing Award Winners (1966-2008) by Country of Affiliation, N=55

Sub-Population	Country of Birth	Country of Ph.D.	Country at the Time of the Award	Number of Turing Award Winners	% of Total Turing Award Winners
Foreign* Scientists	UK	UK	UK	4	7.27
	Israel	Israel	Israel	2	3.64
	Norway	Norway	Norway	2	3.64
	Canada	Canada	USA	1	1.82
	Denmark	Denmark	Denmark	1	1.82
	Greece	France	France	1	1.82
	Germany	USA	Israel	1	1.82
	Netherlands	Netherlands	Netherlands	1	1.82
	Switzerland	USA	Switzerland	1	1.82
Sub Total				14	25.45
American* Scientists	USA	USA	USA	33	60.00
	Canada	USA	USA	1	1.82
	China	USA	USA	1	1.82
	India	USA	USA	1	1.82
	Latvia	USA	USA	1	1.82
	UK	USA	USA	1	1.82
	USA	USA	UK	1	1.82
	USA	USA	Canada	1	1.82
	Venezuela	USA	USA	1	1.82
Sub Total				41	74.55
Total				55	100.00

*I divided Turing Award winners into two sub-populations of "Foreign" and "American" scientists based on their Ph.D. training and work history prior to the Turing Award. The division helped to identify a comparable sample of American scientists that were eligible for comparative analysis (see Chapter 3). This division may not accurately represent nationality since information on nationality was not always available in biographical records.

[n=1], France [n=2], and India [n=1]) of the control group scientists also largely represent the trans-Atlantic "world" of computer science.[123]

Degrees Over Time

All (55) of the Turing Award winners from 1966 to 2008 were college graduates (with various degrees, mostly Ph.D.s) in the period from the 1930s through the 1980s.

[123] Strictly speaking, India is not part of the trans-Atlantic world, unless we consider its past as a British colony and its adoption of English as a second national language. For many years Indian students migrated to United States to study or work in computer-related fields. One Indian scientist from the control group and one Indian Turing Award winner were educated in the U.S. and became accomplished computer science professors in the United States and thus were counted as American scientists.

The next few tables present data on 55 Turing Award winners (data on the control group appears only in comparative analyses with 30 Turing Award winners). The largest number of awardees received their terminal degrees during the 1950s and the 1960s (see Figure 5.1).

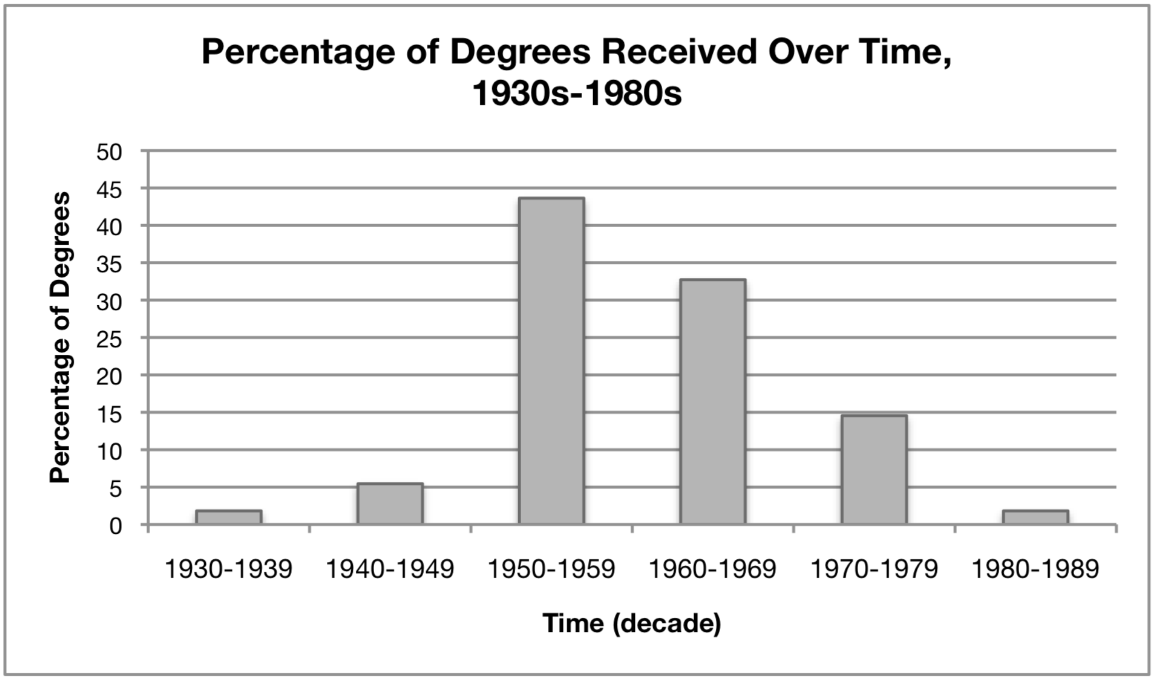

Figure 5.1. Percentage of Terminal Degrees Received by Turing Award Winners (N=55), Over Time (1930s-1980s)

Considering that an average (and median) lag-time from terminal degree to conferral of the Turing Award was about 27 years, 76 percent (of 55) of winners from four decades received their terminal degrees during two decades, the 1950s and 1960s, thus forming a cluster. If the distribution of winners over time was more even, those who graduated during the 1930s and 1940s and did research for 27 years (time-lag) would be expected to receive awards during the 1966-1975 time frame, but the data indicate otherwise. During the first ten years of the award (1966-1975), only four recipients, among the 11 winners, received their degrees in the 1930s and 1940s, six during the 1950s, and one during the 1960s. The clustering can be explained in part by the rapid growth of computer science between the 1960s and 1990s. After launching their careers, graduates in 1950s and 1960s waited an overage of 21 years for their awards, a shorter period than later awardees, possibly because a disproportionate share of opportunities for significant technical contributions to the emerging field of computing opened up in 1950s. By comparison, in the last ten years (1999-2008), the Turing winners received their awards as many as 35 years after receiving their terminal degrees, which can be explained by a number of reasons: 1) increased number of computer scientists, 2) fewer opportunities, in comparision to earlier decades for groundbreaking contributions, and 3) the Turing Committee's ability (e.g., age of committee members) to identify "prominent" researchers.

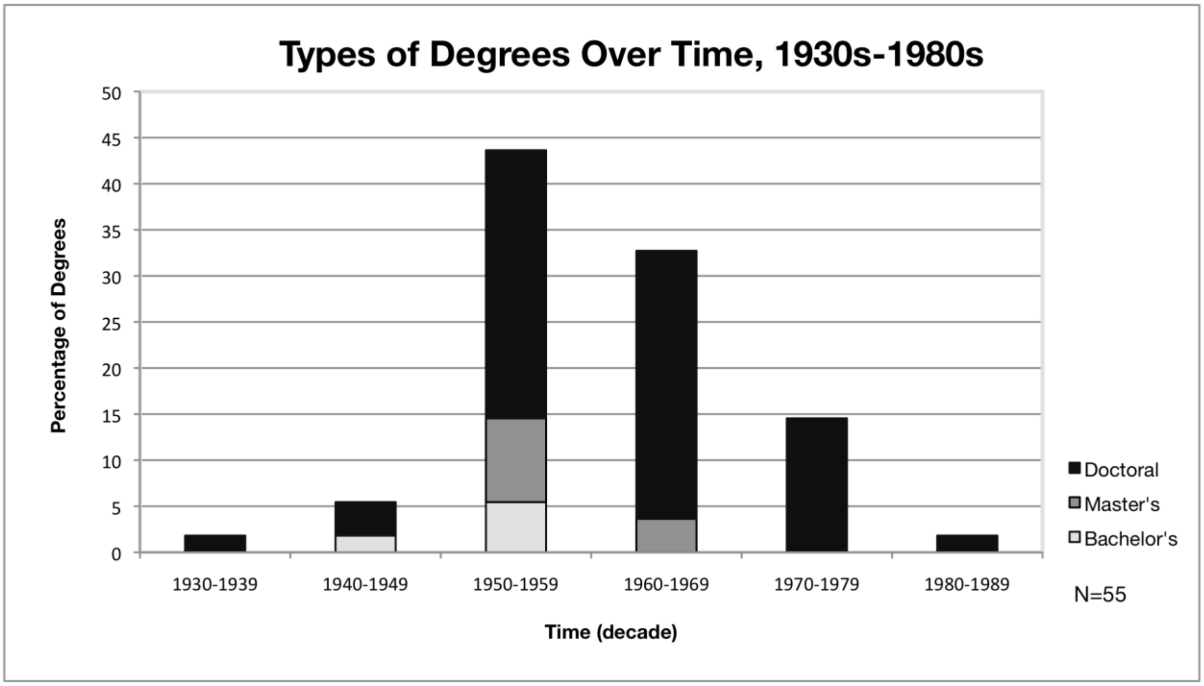

Figure 5.2. Types of Terminal Degrees Received by Turing Award Winners (N=55), Over Time (1930s-1980s)

By examining the types of terminal degrees (Figure 5.2), I found that the majority of Turing Award winners had Ph.D.s as their terminal degree, a few had master's degrees, and four had bachelor's degrees (counting three Oxbridge degrees).[124] By

[124] In the UK, the University of Cambridge, Oxford and Dublin have a provision to confer master of arts degrees on holders of bachelor's degrees seven years after matriculation without any other requirements (except for a payment). These degrees are known as "Oxbridge Master's" degrees. While not all students choose to "upgrade" their degrees this way, some do. Three cases of Turing Award winners from the UK having bachelor's and master's degrees were carefully examined and were counted as bachelor degrees if the master's degree was found to be an upgraded Oxbridge degree. See http://www.admin.cam.ac.uk/univ/degrees/ma/

examining the distribution of types of terminal degrees over time, we can clearly see that those who received bachelor's and master's as terminal degrees did so during the decades of the 1950s and 1960s. In subsequent decades, Ph.D. degrees, especially for the younger awardees, became the standard.

Institutions

By constructing Tables 5.2 and 5.3, I intend to display the distribution of universities attended and degree fields pursued by American and foreign Turing Award scientists. Table 5.2 lists universities where American and foreign recipients of the Turing Award received their terminal degrees.[125] The graduate schools attended by American scientists comprise top research universities with very high research activities.[126] Absent from the list are doctoral-granting universities with less intensive research activities. The high selectivity of universities attended by Turing Award scientists merits attention. Among these universities, we find eight (out of 10) top universities with the highest quality of graduate faculty, and seven (out of 10) of the most effective doctoral programs in computer science, according to the reputational survey of graduate programs in computer science by Richard Conway (1978).[127] All but three American universities attended by Turing Award winners are listed in the top quartile of comprehensive rankings of doctoral research programs in computer science by the National Research Council (Goldberger, Maher, & Flattau, 1995, p. 323). The universities attended by foreign scientists, similarly, constitute the top, best-known schools in their respective countries. Two of the foreign Turing Award scientists who studied in the United States attended very select universities (Princeton and University of California, Berkeley), as did the six control group scientists (Princeton, Harvard (n=2), Carnegie Mellon University, University of California, at Berkeley

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[125] I also examined undergraduate institutions attended by Turing and matched sample of scientists. Unfortunately, data about undergraduate institutions were missing for five Turing and five matched scientists. The available data indicated that twice as many scientists in each groups attended private institutions. There were no other discernable differences between the two groups.
[126] According to the 2005 classification categories of the Carnegie Classification of Institutions of Higher Education, see http://classifications.carnegiefoundation.org/.
[127] See notes on ranking of universities in the Appendix E.

Table 5.2. Universities Attended for the Last Degree Received by Turing Award Winners (1966-2008), N=55

Last Institution Attended	Turing Award Winners (% within column)		
	American (n=41)	Foreign (n=14)	Combined (n=55)
Harvard University, USA	17.1		12.7
Princeton University, USA	12.2	7.1	10.9
University of California at Berkeley (UC Berkeley), USA	12.2	7.1	10.9
Stanford University, USA	12.2		9.1
Massachusetts Institute of Technology (MIT), USA	9.8		7.3
University of Cambridge, UK		21.4	5.5
California Institute of Technology (Caltech), USA	4.9		3.6
Carnegie Mellon University (CMU), USA	4.9		3.6
University of Chicago, USA	4.9		3.6
University of Michigan, USA	4.9		3.6
University of Oslo, Norway		14.3	3.6
Weizmann Institute of Technology, Israel		14.3	3.6
Columbia University, USA	2.4		1.8
Cornell University, USA	2.4		1.8
Duke University, USA	2.4		1.8
University of California at Los Angeles (UCLA), USA	2.4		1.8
University of Copenhagen, Denmark		7.1	1.8
University of Grenoble, France		7.1	1.8
University of Illinois, USA	2.4		1.8
University of Leyden, Netherlands		7.1	1.8
University of Oxford, UK		7.1	1.8
University of Pennsylvania, USA	2.4		1.8
University of Toronto, Canada		7.1	1.8
University of Utah, USA	2.4		1.8
Total	100	100	100

and at Los Angeles). This finding is consistent with prior research that documented the increasing popularity (choice) of American institutions for graduate training among foreign students in the second half of the 20th century (Graham & Diamond, 1997).

Fields

With respect to fields of study (see Table 5.3), the highest percentage of degrees was obtained in mathematics by both American and foreign scientists (42% combined), closely followed by computer science (24%, especially common among the latest prize-winners). The next two most frequently appearing fields were electrical engineering

(11%) and physics (9%). Thus, prior to computer science becoming the expected standard, scientists from mathematics,

Table 5.3. Fields of Study for the Last Degree Received by Turing Award Winners (1966-2008), N=55

Degree Field	Turing Award Winners (% within column)		
	American (n=41)	Foreign (n=14)	Combined (n=55)
Mathematics and Applied Mathematics	41.5	42.9	41.8
Computer Science (CS)	26.8	14.3	23.6
Electrical Engineering (EE) and Electrical Engineering and Computer Science (EECS)	12.2	7.1	10.9
Physics	7.3	14.3	9.1
Classics		14.3	3.6
Industrial Administration	4.9		3.6
Astronomy		7.1	1.8
Communication Science	2.4		1.8
Mechanical Engineering	2.4		1.8
Political Science	2.4		1.8
Total	100	100	100

engineering, physics, and a few other fields conducted research and made significant contributions recognized by a Turing Award in the new and growing field of computer science. Collected data (not shown) also reveals that a large percentage of the American Turing Award winners (85%) earned Ph.D.s in their fields of study while Ph.D. degrees were less prevalent among foreign scientists (64%).

The distribution of fields of degree pursued by Turing Award winners over time (1930s-1980s) is presented in Figure 5.3. One can clearly observe 1) the persistent but subsiding percentage of degrees in mathematics, 2) the diminishing percentage of degrees in physics, and 3) the growing percentages of engineering and computing degrees.

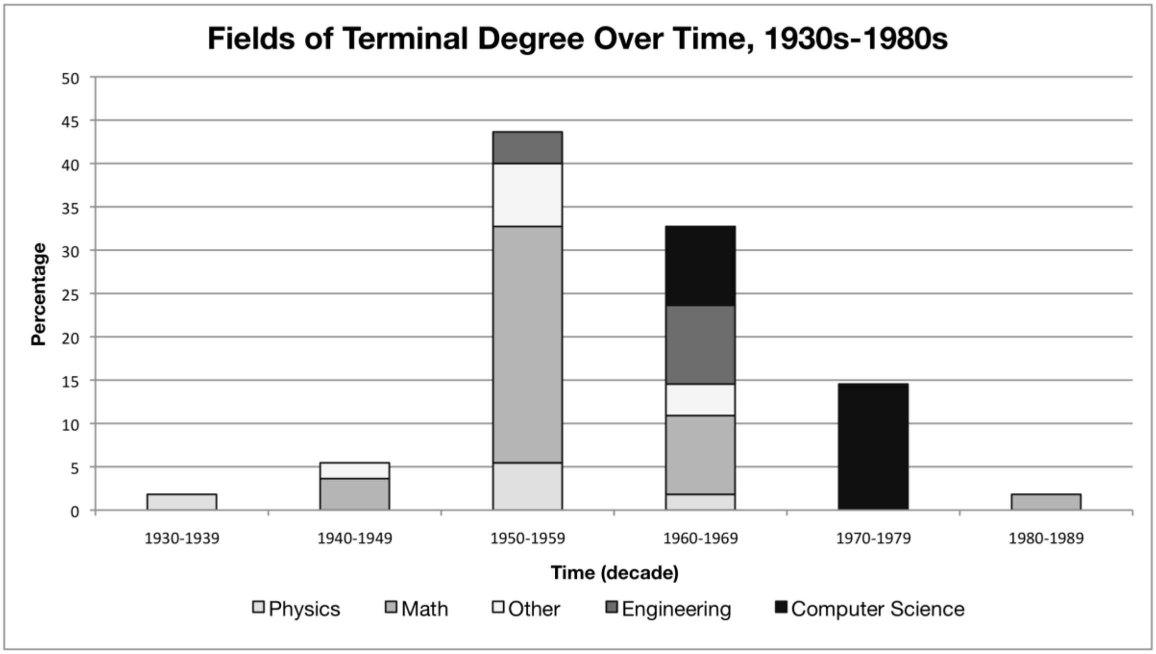

Figure 5.3. Fields of Degree Pursued by Turing Award Scientists (N=55), Over Time

Fellowships and Employment

Funding for research is a vital element of graduate education. In the sciences, sponsored research funding typically supports and trains graduate students involved in projects as graduate research assistants, for which their advisors are principal investigators or co-investigators. Fellowships, on the other hand, provide support for students by allowing them to focus on their own research under the supervision of their advisors. The advantage of having a fellowship, as opposed to a graduate research assistantship, is that in addition to providing financial support, it also rewards a recipient with more freedom and autonomy to pursue research and boosts confidence, as has been reported in interviews (Sonnert & Holton, 1995a). However, some researchers (Gaughan & Robin, 2004) have argued that research assistantships might be more beneficial for graduate students as they provide an opportunity for development of scientific and technical human capital that would be missed by fellowship recipients. Since research assistantships are more common (Gaughan & Robin, 2004; NSF, 2006), for the purposes of this study, I note only fellowships (as a type of exclusive reward).

In the biographies of Turing Award scientists (retrieved from *American Men and*

Women of Science), only three mentioned having a fellowship during their graduate years (at Princeton and Stanford) while none of the control group scientists reported having one. On the acknowledgements page of the dissertations, 16 (46% of 35 with Ph.D.s) American Turing Award winners acknowledged receiving support during their graduate training from various funding sources: five (5) from NSF, four (4) from the military (Airforce, ARPA, Navy), three (3) from corporate sponsors (IBM and Bell Labs), three (3) from institutions (fellowships reported earlier), and one (1) from a non-profit (RAND) research organization.[128] A surprising finding in biographical data was that at least 15 (37% of 41) Turing and 11 (37% of 30) control group scientists were employed, mostly in industry, during their graduate years, possibly within the framework of cooperative education (co-op) which combines classroom and practical training, common in technical schools.[129]

Advisors

One of the most consequential relationships that a scholar develops during graduate training is with his/her advisor. Through the advisor, a student acquires scientific taste, values, norms, and beliefs (Zuckerman, 1977). Furthermore, advisors are instrumental in promoting young researchers:

> Eminent sponsors are not only better equipped by their power and influence to look after their apprentices; they can also increase the visibility of those apprentices. Young scientists are often known, if not finally judged, by the distinction of their masters. And with the growth of big science that brings with it more anonymity, visibility may become increasingly important in the early stages of developing a professional reputation. The visibility conferred by having a well-known master means, among other things, that the young scientists who had not yet acquired a scientific identity will have a better chance of having his work noticed, read, and used than other scientists doing work of the same quality. (Zuckerman, 1977, p. 135)

Given the importance of the advisors in training and placement of students, advisors of Turing and control group scientists are of considerable interest to this study. In career

[128] I did not count university (and external) labs in which research has taken place. Acknowledgement of multiple sources was uncommon. Only one scientist reported having received two fellowships that were counted as one.
[129] I did not count research assistantships as employment.

outcomes, it is important to know if advisors who trained both Turing and control group scientists were productive and eminent scholars. I will use the number of publications and citations (to the most cited publication prior to the Turing Award year) to assess the productivity and impact (one possible measure of eminence) of the advisors of Turing (N=30) and control group students.[130] Since the education of these (Turing and control group) students culminated in a Ph.D., the influence of advisors was likely to be most consequential.

Table 5.4. Productivity and Impact Measures of Advisors of Turing and Control Group Scientists* at Different Time Periods

Measures	Timing of Measurement	
	At the Time (Year) of Turing Student's Graduation	**At the Time (Year) of Student's Turing Award**
Productivity		
Number of Publications in Journals		
Mean	16.7	42.3
Median	13.5	25.5
Impact		
Maximum citations**		
Mean	33.5	231.7
Median	8	57

*The life-long publications and citations (retrieved from the Web of Science) of advisors were counted up to the year of graduation of their students, who are future Turing Award recipients, and up to the year when students received their Turing Award. The citation counts for the time period of 1930-1960s may not be complete because not all journals/publications were catalogued by the Web of Science.
**Maximum citations are given to a single most-cited publication.

Table 5.4 summarizes productivity and impact measures for the advisors of Turing Award and control group scientists (same advisors for both groups). The advisors published on average 16.7 (median 13.5) articles in referred journals by the time of graduation with a Ph.D. of their corresponding (Turing Award) student and about 42.3 (median 25.5) articles by the time (year) when the student received the Turing Award. Considering that many computer scientists (with a Ph.D.) publish very little (Long,

[130] Here I limit my comparison to Turing scientists who were matched with other scientists from the same advisor. I leave out scientists with master's and bachelor's degrees (5), women scientists (2), one social scientist (1) and those who became industry researchers (3).

Crawford, White, & Davis, 2009), these publication rates are higher than the average for scientists in information systems from high status universities 11-15 years after graduation (mean = 2.24, see Long, Crawford, White, & Davis, 2009) but lower than those of scientists and engineers (though foreign) who were promoted to senior research positions (mean = 49, see Jensen, Rauquier, & Croissant, 2009). Given the differences in the number of publications between two time points (at the time of the advisee's graduation and at the time of advisee's award), it is possible to conclude that some advisors were beginning their professional careers when Turing scientists got their Ph.D.s and published much more after their students' graduation.[131]

The citation counts of the most cited publication of advisors were highly skewed at both time points. At the time of graduation of their (future) Turing Award students, 60 percent of the advisors had six or more citations; and only 23 percent of advisors had citations above the mean of 33.5 (the highest citation was 312). At the time of the Turing Award, for 43 percent of advisors, the citation counts were greater than the average for faculty from high status universities (mean =108, see Long, Crawford, White, & Davis, 2009). For the top 30 percent of advisors, between the time of Turing student's graduation and the bestowal of the Turing Award, the citation count grew in orders of magnitude (starting with 169), with the highest citation count being 1,615 for a flagship article introducing information theory by Claude Shannon (not shown). For comparison, "In the 1961 SCI [Science Citation Index] the average reference author [was] cited 5.5 times while recent Nobel Prize winners (1962 and 1963) were cited an average of 169 times" (Garfield, Sher, & Torpie, 1964, p. iv). I conclude that the majority (60%) of advisors had at least one well-cited publication but fewer (23%-30%) advisors were (or became) eminent researchers[132] at the time of graduation of their Turing students (or by the time students received their Turing Award).

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[131] I also do not discount the fact that publication expectations were lower in 1930s-1960s compared to current standards.

[132] The "eminent" title refers to 23% of advisors whose number of citations of their most cited publications was above the group average of 33.5 at the time of the graduation of their students with a Ph.D. By the

We may also compare the productivity and impact measures of advisors to those of their Turing Award students. As expected, the average citation counts of Turing Award recipients (198.5) at the time of the Turing Award are higher than those of their advisors at the time of graduation (33.5) but not at the time of the award (231.7) (see Table 6.3 for data on Turing Award students). Similarly, the number of publications (28.23) of Turing students at the time of the award exceeded that of their advisors at the time of awardees' graduation (16.7) but not at the time of the award (42.3) (Turing Award winners received their Turing Award in the mid-end of their careers).[133]

Advisors were no strangers to the Turing Award. About 27 percent (n=8) of advisors of future winners also received a Turing Award, and 30 percent (n=9) had more than one student who won a Turing Award. These patterns indicate a significant amount of continuity in research lineage among awardees (similar to Nobel laureates, see Zuckerman, 1977).[134]

Publications with the Advisor

To investigate if productive/eminent advisors produce productive or eminent students, I examine the relationship between productivity and eminence of advisors and the productivity and eminence of the advisors' students. To get some sense of this relationship, I compared four groups of advisors—those with high and low productivity (based on the median[135] number of articles published by all advisors prior to the year of the Turing Award of their students) and those with high and low citation impact (based

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time their students received the Turing Award, about 30% of advisors' citations were above 169, the average number of citations of Nobel Prize winners for 1962-1963 (for all of their publications). The averages of all citations of advisors' publications were likely to be lower than those of Nobel Prize scientists.

[133] I attribute citation differences to smaller size of computing academic community and possibly greater fragmentation within it. The differences in publications can be attributed to the fact that the Turing Award most often comes in the mid-late career while the data for advisors were collected for mid-early and very late stages of their careers.

[134] Additional evidence for this comes from acknowledgements pages of dissertations of Turing Award scientists where I counted 18 mentions of Turing Award scientists who served either as a committee member or as a mentor or a friend.

[135] The median was calculated for the group of advisors (N=30).

on the median maximum citation count of a single publication of all advisors prior to the Turing Award year)—to the productivity and impact of their students.[136]

I divided the group of 30 advisors according to the number and impact of their publications (high productivity: number of publications is above the median=25.5; low productivity: number of publications is below the median=25.5; high impact: max citation count is above the median=57; low impact: max citation count is below the median=57, see Table 5.4). Similarly, the Turing and the control group students of advisors were divided into comparable groups based on the combined group medians of their publication and citation counts. The results of classification of advisors and their students, those who received the Turing award and those who did not, are displayed in Table 5.5. Table 5.5 indicates that highly productive scientists-advisors, who are also highly eminent, cultivated more productive and/or eminent (as opposed to not productive/eminent) scientists-students (27% of Turing scientists and 23% of the control group, percentage was added horizontally but not shown in the Table). The same is true for highly eminent scientists-advisors who cultivated productive, eminent, or both scientists-students (13% of Turing scientists and 6% of the control group). Surprisingly, advisors with low productivity and low impact cultivated more productive and/or cited students than highly productive but not cited scientists-advisors (17% versus 6% among Turing scientists and 13% versus zero among control group).[137] These findings, albeit interesting, should be treated with caution because only two (Turing and control group) students were selected while advisors had other students whose outcomes were not considered.

[136] Productivity and impact differences prior to the year of Turing Award were more pronounced and were chosen for these sets of analyses. I did not use graduation year indicators because they could not capture numerically the productivity of advisors since many advisors appeared to be in the mid-beginning of their careers.
[137] Though they were not great researchers they may have been good teachers.

Table 5.5. Productivity and Impact Measures for Turing Award (N=30) and Control Group (N=30) Students Compared to Their Advisors (N=30)

Advisors	Turing Award Students (n=30)				Control Group Students (n=30)			
	HIGH prod./ HIGH impact (%)	HIGH prod./ LOW impact (%)	LOW prod./ HIGH impact (%)	LOW prod./ LOW impact (%)	HIGH prod./ HIGH impact (%)	HIGH prod./ LOW impact (%)	LOW prod./ HIGH impact (%)	LOW prod./ LOW impact (%)
HIGH productivity, HIGH impact (n=10)	20	7		7	13	7	3	10
HIGH productivity, LOW impact (n=5)	3		3	10				17
LOW productivity, HIGH impact (n=5)	3	7	3	3	3		3	10
LOW productivity, LOW impact (n=10)	7	3	7	17	7	3	3	20

Note: Productivity and impact measures of students are based on publication and citation counts prior to the year of the Turing Award.

The sub-sample of advisors who published with their students (N=13) is of great importance to this study because publishing with an advisor is likely to advance the career of an advisee. Collected data indicate that nine (9) out of 30 (30%) Turing winners had publications with their advisors prior to or two years after graduation, while only four (4) out of 30 (13%) control group scientists had published with their advisors during this same time period. Thus, Turing Award winners were twice as likely to publish with their advisors compared to the matched scientists. In both groups (winners and non-winners), those who published with their advisors often had not just one article, but two or three publications (co-authored with advisors) within the first two years after graduation. As seen in Table 5.6, all of the advisors (N=13) who published with their students were highly productive or highly eminent, and so were most of their students (78%, rounded; low productivity and low impact students were not counted).

Table 5.6. Productivity and Impact Measures for Turing and Control Group Students Who Published With Their Advisors (N=13) Compared to Their Advisors (N=30)

Advisors	Turing Award and Control Group Students who published with their advisors			
	HIGH productivity/ HIGH impact (%)	HIGH productivity/ LOW impact (%)	LOW productivity/ HIGH impact (%)	LOW productivity/ LOW impact (%)
HIGH productivity, HIGH impact (n=8)	46	8		8
HIGH productivity, LOW impact (n=4)	8		8	15
LOW productivity, HIGH impact (n=1)		8		
LOW productivity, LOW impact (n=0)				

Note: Productivity and impact measures of students are based on publication and citation counts prior to the year of the Turing Award.

Scientists' First Job

Advisors were often instrumental in launching the careers of Turing Award scientists by introducing them to the field, as described by one Turing Award winner:

> I was a graduate student in the newly formed Computer Science Department at Berkeley. ...Mike Harrison was my advisor. It was an interesting group of people. Steve Cook, Dick Karp, Butler Lampson [all Turing Award winners], and Jim Morris were on the faculty. The people at Stanford were pretty astonishing, and we were on pretty good terms with them. We had reasonably good contacts with MIT and UCLA. It was a very small world. Something, I guess, that is difficult to grasp these days. Everybody knew everybody. One had even a stronger feeling of that back in the 1950s. They had these conferences where quite literally everybody in the field showed up at the conference. Even in the 1960s Mike Harrison knew lots and lots of the principals. Through him I met many of the principals in the field. Mike was quite close to Seymour Ginsburg who was one of the leaders in the field in formal language theory. I got to take classes from Dick Karp, Steve Cook, Mike Harrison, and Butler Lampson. It was really a great education. (Gray, 2002, p. 14)

Getting a "good" first job in a prestigious organization not only sets the starting point of one's career, but also influences subsequent research productivity. However, researchers also have found that first jobs more strongly correlated with the prestige of a scientist's doctoral institution than with his/her prior productivity (Long, Allison, & McGinnis, 1979). Since Turing scientists and the control group come from the same institution, theoretically, they are likely to have similar chances of getting a "good job." However, as we can see from Table 5.7, more than twice as many Turing Award scientists (47%), compared to non-winners (20%), found first research and teaching jobs at the top five academic institutions in computer science. Thus, students of the same advisors faced differing career prospects. It is also possible that research area (problem choice) of some students was more favorably perceived by hiring institutions than of others. The chances of finding work in home institutions were surprisingly similar: the same percentage of Turing Award scientists (23%) and control group scientists (23%, data not shown) were hired by the same institution where they received their graduate degrees (this includes "holding" positions in the same institutions prior to moving to another position). Being hired by the institution granting the Ph.D., or by one of similar status, is consistent with prior findings that most prestigious departments at that time mainly hired graduates from similarly prestigious departments (Burris, 2004; Crane, 1970; Long, 1978; Long, Allison, & McGinnis, 1979; Long & McGinnis, 1981) or their own Ph.D.'s (Burris, 2004; Hargens & Farr, 1973; McGee,1960;). Table 5.7 indicates that scientists from the

Table 5.7. Place of First Job of Turing Award (N=30) and Control Group (N=30) Scientists, 1930s-1980s

	Scientists (% within each group)	
Place of First Job	**Turing Award Winners (n=30)**	**Control Group (n=30)**
Top Five* Universities in Computer Science	47	20
Top Quarter* of Universities in Computer Science	20	33
Other Universities (below top quarter)	13	20
Government and Academic Labs, Military Agencies, and Think Tanks	10	13
Industry	10	13
Total	100	100

*According to the National Research Council's ratings (see Goldberger, Maher, & Flattau, 1995). The top quarter of universities does not include top five university programs that are listed separately.

control group were more likely to find first jobs in less prestigious[138] universities (that were building their programs in computer science and recruiting new faculty, see chapter 2) as well as in academic laboratories,[139] the military, and in industry (also see chapter 6).

DISCUSSION

Higher education is an important stage of one's professional career because formal graduate training is often a requisite for admission into the ranks of professional scientists. This chapter provides (to the best of my knowledge) one of the first accounts of the educational attainments of this group of distinguished computer scientists, the recipients of the Turing Award from 1966 to 2008. The aim of the chapter is to identify which educational factors were associated with and differentiated the winners of the Turing Award from the control group of computer scientists. Some of the findings emerged from descriptive analyses for all 55 Turing Award winners and others from the comparative analyses of 30 American Turing Award and control group scientists. Because Turing Award scientists were matched on the bases of having attended the same institutions and being supervised by the same advisors, comparative findings reflected the differences between 30 American winners and 30 control group scientists, while the descriptive results referred to all 55 Turing Award winners.

Descriptive Results

Although the Turing Award has been bestowed for nearly four and a half decades (1966-2008), 76 percent of recipients received their terminal degrees in a period of only two decades, in the 1950s and the 1960s, reflecting the rapid growth of the computing field. Turing Award scientists pursued a range of degrees whose popularity (based on how often it was chosen as a terminal major that may reflect a demand for trained professionals in that area) changed over time. Prior to the establishment of computer

[138] University programs that are rated below top quarter in computer science by the National Research Council (see Goldberger, Maher, & Flattau, 1995).

[139] The "academic laboratories" include MIT Lincoln Labs, where two control group scientists became members of technical staff.

science departments, many Turing Award scientists received their terminal degrees in mathematics, engineering, and physics. This is quite consistent with the report published by the National Science Foundation (2006), describing the history and growth of doctoral education in the United States from 1900 to 1999. The report revealed that from 1920 until the early 1960s, physical sciences led all other major fields in doctoral degrees; however, engineering has been growing since the 1950s and by 1995–1999, it had replaced physical sciences among the top five major fields (NSF, 2006, p. 14). Over the years, as the prominence of physics diminished (NSF, 2006),[140] the percentage of degrees in physics among Turing Award winners decreased. At the same time, as the prominence of engineering and computer science degrees increased, the percentage of degrees in these disciplines among award winners also rose. The standardization of credentials (i.e., the expectation that to do research in computing, one needs a degree in computer science) is evidenced by the increasing prominence of Ph.D. degrees in computer science. The changes in the fields of study of Turing winners reflect the growth and development of computer science as a field. As new knowledge becomes codified, as it did in computing, the professionals' dependence on formal training increases (Larson, 1977).[141] As a result, we are likely to see Ph.D. degrees become a prerequisite for research positions in computer science.[142]

The data collected also revealed that the majority of award winners were American scientists (75%), while international winners (25%) mainly represented other trans-Atlantic countries (Canada, Denmark, Israel, Netherlands, Norway, and United Kingdom). After World War II, the United States had more resources than any of the European countries to invest in building new computing machines and making them available to universities. Not surprisingly, among those foreign students who chose to attend U.S. graduate schools, we find foreign Turing Award winners (14%), and foreign

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[140] See Appendix H about the changes in the doctorates awarded from 1920 to 1999.

[141] Larson notes that accepted professionals "increasingly tend to come from the centers which monopolize the production and transmission of knowledge" (Larson, 1977, p. 45). The recognition of a peer as exceptional comes with a judgment from inside which cannot be questioned "without questioning the profession's internal stratification" (Larson, 1977, p. 45).

[142] See Appendix I on the deviations and importance of degrees for careers of Turing research scientists.

students from the control group (20%) (not counting 15% of American Turing Award winners who immigrated from other countries).

Similar to Nobel laureates examined by Harriet Zuckerman (1977), eminent computer scientists received their training at a few top institutions. The 41 winners from the United States attended only 16 institutions. The institutions attended by the winners were largely the same elite institutions attended by Nobel Prize winners (Zuckerman, 1977, p. 90) and a few other universities well-known for their computer science departments, such as Stanford University, Carnegie Mellon University (CMU), Duke University, University of California at Los Angeles (UCLA), and the University of Utah. The question arises as to why so few elite institutions produced so many Turing Award scientists? Two mutually supportive explanations may apply: 1) these were the best-known schools offering computer science curriculum, and 2) Turing scientists were selective in their choice of the best computer science program. The first has to do with historical visibility, prestige, and the ability of large elite schools to attract sponsors for building (or donation) of computers and to be the first to offer computer training. As described in chapter 2, during the early years (1950s), only a few schools, those with federal funds or industry resources, obtained computers and provided training in computer science. Over the years, students aspiring to higher degrees came to learn that the top schools in computing were schools such as Stanford, Massachusetts Institute of Technology (MIT), University of California at Berkeley, Carnegie Mellon University, and Cornell. These universities, which were the first to offer a computer science curriculum (early entrants), gained great marketing value and prestige (Aspray, 2000), and constituted the top of the hierarchy of schools in computer science. This high ranking has persisted through time with little change.

The second explanation has to do with observations made of Nobel laureates, another elite group of winners who, as graduate students, exercised greater selectivity in their choice of schools for graduate education (Zukerman, 1977). When a bright student wants to do serious work, he or she chooses a top school and a famous and talented advisor. A similar selection may have taken place among Turing Award winners. For example, as Ivan Sutherland, a student of Claude Shannon at MIT, stated, "The reason I left Caltech and went to MIT was it was clear that computing at MIT was better than at Caltech at that time, and it was a clear-cut case of the right thing to do" (Aspray, 1989, p. 3). This pattern of mutual selection between individuals and organizations was observed by Harriet Zuckerman (1977) who noted that the "two stratification hierarchies—of individual and organization—are in fact tightly interconnected through exchanges of prestige and through self-selection and selective recruitment" (p. 250). In the efforts to improve their prestige ranking, university departments compete for the best students because successful graduates will add eminence to the department and university by their future achievements (and positions in top computing companies). At the same time, students who attended those universities had much to gain from quality, research aspirations and the prestige of top-ranked departments.

Comparative Findings

a. Fellowships

A small percentage of Turing scientists from very select schools were supported by university fellowships (10%) while others worked on sponsored research (at least 43%). While fellowships testify to an exclusive form of support and devotion to one's studies, working (outside of graduate research) while in graduate school was not uncommon (at least 37% of 41 Turing and 37% of 30 of control group scientists worked while in graduate school). The availability of work testifies to the demand for trained professionals, and the importance and ease of the transferability of skills (computer, math, physics) to the job market.

b. Advisors

The data collected on advisors confirmed that some Turing Award scientists studied under the guidance of distinguished advisors (23%-30%). In top research universities, students have access to the considerable intellectual resources, scientists "of caliber" similar to those acknowledged by Marvin Minsky (1954), Turing winner from 1969, in his dissertation at Princeton university:

I am gratefully indebted to Dr. G. A. Miller for his encouragement and counsel from the time this work was first considered, and to Dr. A. W. Tucker for his encouragement, criticism, and for his deft removal of obstacles. Much of the material in this work stems from extended discussions and arguments with Drs. John McCarthy, John Nash, John von Neumann, Claude E. Shannon, John Tukey, and David L. Yarmush.

Given that at the time of Turing scientists' graduation, the advisors were likely to be in the beginning of their careers, advisors' publication and citation statistic indicate increased eminence later in their careers (measured up to the year when their Turing students received their awards). By the time their Turing Award students received their awards, about 86 percent of the advisors (of Turing Award and control group scientists) had a publication that was cited above an average rate for scientists in 1961, and about 30 percent of advisors had a publication that was cited above the average citation rate of Nobel laureates.[143] In addition, about 30 percent of advisors either received a Turing Award or had more than one student who won the Turing Award, indicating the existence of social ties and lineage of prize worthy research.

The student-advisor relationship is at the core of scientific graduate education (Fox, 2003). Because the alignment of timing, interests, and choice of research topics is different for each student and because graduate experiences may vary with the same advisor, I do not expect all students to attain the same level of success as their advisor (i.e., in both productivity and impact). However, the evidence presented in this chapter, no matter how small, supported the argument that more productive and cited advisors tend to train more productive and/or cited students (as opposed to less productive and cited students). Furthermore, advisors who had published with their students were more productive or more cited and so were the great majority of their students (78%). These observations draw attention to "sorting" and matching of students and advisors and training of the next generation of productive scientists:

> Thus, the training of a scientist may be regarded as an increasingly selective process in which most of the best students are channeled into the best graduate schools and, in turn, the best of these

[143] The rates used for comparison are those reported by Garfield, Sher and Torpie (1964) from 1961 *Science Citation Index*. Admittedly, these are equivalent comparisons as the citation rates reported by them were based on averages of all publications of many scientists while this study used the maximum citation to a single publication.

> are selected for training by the top scientists. This highly select group becomes the next generation's most productive scientists, most frequently chosen for positions in major universities. (Crane, 1965, p. 705)

The matching has implications for supporting productivity and eminence (impact) of current and future faculty, that is, supporting success (productivity and impact) of current faculty is important for training the next generation of scientists. The matching also prompts questions for post-dissertation research as to how excellence is defined in students (what is the "best"), how students are matched with advisors and in what ways advisors are influential (that is, how advisors facilitate success and excellence in their students).

c. First Jobs

High selectivity of graduate institutions among Turing Award winners is likely to be consequential for later career attainments. The connection between educational and career attainments have long been established by researchers who have found that an individual's undergraduate and graduate education influences later occupational attainments of prestige and income (Blau & Duncan, 1967; Duncan & Hodge, 1963). The prestige of the university attended matters because the perception of talent often comes from "the reputation of the institution where a professional has been trained" (Larson, 1977, p. 44). The reputation of graduate schools matters because as graduates self-select themselves for different positions, they are also selected by organizations and, as a result, face differing chances of making important professional contributions to research frontiers (that later could make them eligible for awards). Although graduating from the same university, Turing Award scientists were more successful than the control group in securing jobs in prestigious research universities: twice as many of them secured positions in (top) academic institutions that were more strongly aligned with research (Table 5.7).[144] Since Turing Award winners mainly attended top select research

[144] The next chapter provides additional information about organizations where Turing and control group scientists worked.

universities, the chances of receiving a Turing Award of those who did not attend top research universities may be even smaller.[145]

CONCLUSION

In this chapter, I examined the educational factors that differentiate the winners of the Turing Award from those of the control group of scientists who were trained in the same institution with the same advisor. In chapter 1, I hypothesized (*H1*) that Turing Award scientists, compared with the control group scientists (controlled for their institutions, the status of their departments, and eminence of their advisors), would have begun their careers with small advantages such as a fellowship, a publication with their advisors, or a first job in the top five programs (universities) in computer science, each of which may have become crucial (leading to publications and awards) in their later careers. The findings in this chapter revealed that Turing Award scientists as a group were more "successful" in their educational attainments than those of the control group in the following ways: 1) more Turing Award scientists received fellowships (10% compared to 0%); 2) twice as many of them published with their advisors; and 3) twice as many of them (as the control group scientists) found jobs in the top five computer science departments in the United States. These findings indicate that Turing Award scientists were included into research and organizations in science early in their careers, thus testifying to the emergence of disparities between the Turing and the control group scientists during their higher education. Upon graduation with terminal degrees, Turing Award scientists had more early career advantages than the control group, providing

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[145] In many states, educational institutions are structured "hierarchically" (according to a certain mission) allowing only some schools to be research universities. As an example, under pressure to expand engineering education during the Cold War Era, California's public system of higher education, based on a tripartite division (junior colleges, state colleges, and the University of California system), preserved the division between research and vocational engineering schools (Akera, 2010). Thus, students who did not enter research universities were not trained to do research. Such institutional design may avoid overlap and competition among universities for funding, but it may also pre-select students for supportive jobs (as opposed to research), and thus set those students on different paths. As a result, into the future, they may not be eligible for recognition for technical achievements with a Turing Award.

descriptive statistical[146] evidence supporting my hypothesis (*H4*) and the findings of prior research on elites (regarding the importance of early career advantages in scientific careers, see Zuckerman, 1977, 1988). In the next chapter 6 on careers, I will assess how crucial these differences in educational attainments were with regard to the receipt of the Turing Award.

[146] A t-test for the equality of means between two groups revealed significant differences in regard to the first job (p<.05) and for the early career advantage score overall.

CHAPTER 6

CAREER ACHIEVEMENTS OF THE AWARDEES

Formal education, examined in the previous chapter, described the educational background with which the Turing and the control group of scientists entered the job market. In this chapter, I will examine career accomplishments of the two groups, beginning with their post-doctoral employment and assess how early career advantages, reported in the previous chapter, and other professional factors, are related to the likelihood of being a Turing Award winner. The focal question of this chapter is: Which factors (educational and career-related, including collaboration) are associated with and differentiate the winners of the Turing Award from the control group of non-winning computer scientists?

INTRODUCTION

Careers have been defined as a "movement though structures" (Strauss, 1975, p. 81), usually arranged in a hierarchy of prestige. These structures commonly consist of a variety of organizational settings where scientists and engineers work: academia, industry, the government, the military or non-profit sectors. The organizations within each sector differ in size, mission, and their focus on research and development. Consequently, the prestige and visibility of organizations as well as their research orientation and the alignment with criteria of success in a profession are likely to affect careers of employed scientists. The professional success of individuals and the orientation of their employing institutions are ultimately linked (Hermanowicz, 1998, 2009), demanding attention to employing organizations when considering achievements of individual scientists.

Despite their differences, scientists in a variety of workplaces regard the recognition of their professional achievements among the highest professional rewards. All scientists, either directly (through self-nomination) or indirectly (through nomination by a colleague), compete for social recognition of their achievements (Hagstrom, 1965), for such recognition reflects the fulfillment of one's professional role (Merton, 1957/1973). As conveyed earlier, the Turing Award, bestowed for contributions of a technical nature in the computing field, is a high form of professional recognition. This award is not limited to academic scientists; it also recognizes potentially contributions of computer professionals employed in government, non-profit, and various business organizations.

Unlike other organizational rewards (e.g., certificates of recognition, promotion or bonuses) that are more timely or “proximate” to an achievement, recognition in the form of the Turing Award usually comes much later in a scientist’s career. Because the Turing Award citations do not specify the exact year of the contribution, it is difficult to determine the number of years passed from the year of contribution to the year of recognition with the award. However, it is possible to calculate for Turing Award winners the number of years passed from the time of graduation with a Ph.D. degree to receipt of the award. Some Turing scientists received the award in as few as 11 years after earning their Ph.D. while others waited as long as 49 years. The average was about 27.6 years from the time of graduation with a Ph.D. to receipt of the award (see chapter 4). Thus, the award, marking significant technical achievements, is bestowed closer to the end of one’s professional career. Considering that the average age of award recipients was 54.5 and that the award is given annually to a living person, scientists have a limited number of years to receive this award during their lifetime.

Although many scientists believe that success in science is a matter of chance or fate (Hamming, 1986; Sonnert & Holton, 1995a), some factors in professional/scientific careers may facilitate or impede recognition. To address the second question of this study—which factors are associated with the career outcome of becoming recognized by the Turing Award—I will test a set of hypotheses and corresponding measures that have been found to contribute to success in science. According to the norm of universalism in science, rewards are given for performance, which means that productivity and impact (usefulness) of research remain the standard metrics of scientific performance (Cole & Cole, 1973; Long, Allison, & McGinnis, 1979; Long, 1992; Merton, 1973; Sonnert, 1995c). Accordingly, I will test the importance of having *superior productivity prior to the award year (H1)* and having *a high impact publication measured by citations (H2).*

Since advantages were found to accumulate in scientific careers and favor the most eminent scientists (Merton, 1973; Zuckerman, 1977), I will test the importance of *early career advantages (H4), prior awards (H5),* and *employment in an elite university* at the time of the award *(H6).* The usefulness of social capital (in the form of collaborators-coauthors) in accessing resources has been long established (Burt, 1992; Coleman, 1988, 1990; Granovetter, 1973, 1985; Lin, 1999, 2001; Lin, Ensel, & Vaughn, 1981; Lin, Vaughn, & Ensel, 1981). However, the extent of the connection between former collaborators and receiving recognition remains an important question. I will test the effect of *the number of collaborators (H3a)* and *the type of collaborators (H3b).* Further, since the award is given by an organization, *visibility in ACM (H7)* is of importance for being considered for, and receiving, the award. Because both the Turing Award and control group scientists went to the same (major) university and were trained by the same advisor, any productivity differences between Turing and control group scientists are likely to be due to factors other than the graduate university and having a given advisor. In this chapter, I will examine particular factors that potentially contribute to professional success in science: early career advantages, productivity, prior eminence, sponsors among collaborators, institutional location at the time (year) of the award, and scientists' visibility in the professional community (ACM).

BACKGROUND

I provide information on sectors of employment and institutional units as part of the background for this chapter. I consider this information background because it is not part of my hypotheses but represents additional observations that I made while working with the data, and thus is tangential to the question explored in this chapter. I will briefly survey the organizations in which Turing and control group scientists worked to determine any notable differences between the groups in the organizations and sectors of the economy in which they were located (from the time of graduation to the year of the award and an equivalent number of years for the control group scientists). Were Turing scientists, compared to the control group, located in a particular sector(s) or organization during their careers leading to the Turing Award? Were the missions of these organizations aligned with their research in a way that would benefit the careers of award-winning scientists?

Organizations are important to the study of recognition because a) they may facilitate or impede recognition by supplying mundane or challenging problems and distributing work and rewards and b) they have their own systems of rewards (organizational as opposed to professional) to which employed scientists conform:

> As a professional, an individual acquires stature from his [her] colleagues in the profession. As an employee, he [she] acquires status from his [her] superiors in the organization. A series of accomplishments and rewards in the profession constitutes a "successful" professional career. A series of progressively higher positions in the organization constitutes a "successful" bureaucratic career. The contingencies of a professional career are not the same as those of a bureaucratic career, and may conflict with them. Therefore, career lines of professionals in large organizations influence their motivation for professional work. The capacity of the work establishment to define the status and career of its professional employees is at the same time a way of motivating them toward the organization's objective. (Kornhauser, 1962, p. 117)

As a result of having both professional and organizational roles, researchers working particularly in non-academic[147] organizations often experience tension between their professional goals and the organizational objectives (professional goals of producing and publishing one's research may interfere with organizational objectives to meet earnings targets, deliver products, and to protect organizational intellectual property by not making the results public [see Lee, 1969; Mudambi & Swift, 2009]). Turing and control group scientists could have been differentially affected by this tension (for example, the tension is likely be stronger in less research intensive organizations). Although I do not intend to examine this tension, I aim to provide some information about the organizational contexts in which achievements of computer scientists took place.

Sectors of Employment

A distinctive feature of careers of computer scientists is their capacity to move among sectors.[148] The group of winners and control group scientists frequently moved

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[147] Researchers working for academic organizations may also experience tension between their professional goals of doing research and 1) teaching or 2) service, or 3) administration.

[148] Turing scientists held an average of 4.1 positions (a median of 4) while the matched sample had fewer, an average of 3.8 positions (median 3.5). These data include both careers within a given organization and

from academia to industry, and vice versa. Table 6.1 shows that over the course of their careers (prior to the award year), Turing Award scientists spent more time in industry, academia, nonprofit, and military sectors than the control group. The control group scientists, on the other hand, spent more time in the government sector (e.g., agencies and labs) and being self-employed (e.g., consulting and owning a business).

Table 6.1. Years of Experience of Turing and Control Group Scientists in a Sector as a Percentage of Work History (from Graduation Year up to the Year of the Turing Award)

Sector of Employment	Scientists (% of Total Years of Work History for Each Group)	
	Turing Award (n=30)	Control Group (n=30)
Academia	72.7	72.1
Industry	18.1	13.6
Government	0.3	4.7
Military	2.4	1.2
Non-profit	4.8	3.7
Self-employment	1.7	4.8
Total	100	100

Institutional Units

To provide information on where winners and non-winners worked and to compare their work environments, I classified the types of organizational units in which the two groups were employed (as researchers or research leaders) since graduation to the year of the Turing Award (and an equivalent number of years for the control group).[149] Working in the academic sector does not always indicate a professorial position in a department. A scientist may also work in a university-affiliated research center or laboratory. As Table 6.2 indicates, non-Turing scientists

across different organizations, and thus a combined organizational (within an organization) and professional (across organizations) career mobility based on what scientists reported in their biographical profile. Some scientists listed various titles they held within the same organization while other scientists had few titles but more organizational changes.

[149] It was difficult to classify job titles held because 1) in some cases positions were omitted, 2) often positions overlapped, and 3) over seven decades, job titles changed substantially in the computer industry.

Table 6.2. Years of Experience of Turing and Control Group Scientists in Different Institutional Units as a Percentage of Work History (from Graduation Year up to the Year of the Turing Award)

Institutional Unit	Scientists (% of Work History for Each Group)	
	Turing Award (n=30)	Control Group (n=30)
Academic Department	69.9	65.6
Laboratory or Computation Center	3.2	10.3
Institute or Foundation	4.7	5.3
Government Agency or Department	2.3	2.3
Corporation	19.1	14.3
Other*	0.8	2.2
Total	100	100

*The "Other" category reflects different self-employment arrangements such as entrepreneurship (starting one's own company) or a consulting business.

spent more time in (computer) laboratories/centers[150] while Turing scientists spent more time in academic departments and industry. In addition, within industry, Turing Award scientists were more likely to have worked for IBM (often in Watson Research Center), specifically, while none of the control group scientists worked in that setting (not shown).

FINDINGS

Group Profile And Characteristics Of Turing Award Winners And Non-Winners (Descriptive Statistics)

To compare the careers of Turing Award and control group scientists, I examined their career attainments in 1) early career advantage, 2) publication productivity, 3) impact of the most cited publication, 4) eminence, 5) number and type of collaborators, 6) institutional location, and 7) visibility in ACM—prior to the year of the award or in the equivalent number of years for the matched scientists. Table 6.3 provides a summary of these career dimensions.

[150] Computer laboratories/centers are often separate unites within academic and government organizations and have their own structures and missions; they also conduct experimental work or provide support to other researchers or units.

Table 6.3. Descriptive Statistics, Career Measures[151] for Turing Award and Control Group Scientists

Career Measures	Turing Award Scientists (n=30)				Control Group (n=30)				
	Mean	Median	SD	Sum	Mean	Median	SD	Sum	T-test for Equality of Means, t (df=58)
Early Career Advantage Index	.87	1	.73	26	.33	0	.55	10	-3.2**
Fellowships	.10	0	.31	3	0	0	0	0	-1.8
Publications with advisor (y/n)	.30	0	.47	9	.13	0	.35	4	-1.6
First job in top 5 (elite) depts.	.47	0	.51	14	.20	0	.41	6	-2.2*
Productivity									
Publication rate	1.22	.90	1.14	36.6	.84	.45	.95	25.3	-1.4
Publications total	28.23	22	19.27	847	21.5	12	24.93	645	-1.2
Impact									
Citations (max)	198.5	80	337.17	5955	90.87	25.5	177.07	2726	-1.8
Eminence									
Awards total	2.23	2	1.96	67	.43	0	.82	13	-4.6***
Honors and fellowships	1.70	1.50	1.70	51	.40	0	.72	12	-3.8***
NAS and NAE memberships	.53	.50	.57	16	.03	0	.18	1	-4.6***
Location in an Elite Institution									
Employment in top 5 (elite) depts at the time of the Turing Award	.50	.50	.51	15	.13	0	.35	4	-3.3**
Number & Type of Collaborators									
Number of Co-authors	25.7	23.5	19.13	770	14.9	7	16.17	446	-2.4*
Co-authors Already Turing Award winners	.80	0	1.27	24	.30	0	.702	9	-1.9
Co-authors members of the Turing Committee	.50	0	1.08	15	.07	0	.25	2	-2.1*
Visibility in ACM Index	1.30	1	.54	39	.77	1	.86	23	-2.9**
ACM publications	.97	1	.18	29	.57	1	.50	17	-4.1***
ACM awards	.33	0	.58	10	.13	0	.43	4	-1.6
ACM services	.03	0	.18	1	.10	0	0.31	3	1

[151] Career measures reflect life-long achievements up to the year of the Turing Award and an equivalent number of years for the control group.

Early Career Advantages

As reported in the previous chapter, Turing Award scientists were far more likely to secure an institutional fellowship (10% compared to 0 in the control group), and twice as likely to publish with their advisors[152] (30% compared to 13%). Even though Turing and matched scientists entered the academic sector at the same rate of 80 percent following receipt of their Ph.D.s (see Table 6.4), two times as many of Turing Award scientists (47% out of 14) secured their first positions in the top five computer departments in the country compared to the control group (20% out of 6; not shown, see chapter 5). As such, Turing Award scientists as a group had more early advantages as they entered the job market.

Table 6.4. Sectors of Employment of Turing and Control Group Scientists for their First Jobs, 1930s-1980s

Sector of Employment	% of Turing Award Scientists (n=30)	% of Control Group Scientists (n =30)
Academia	80	80
Industry	10	13
Government	3.3	-
Military	3.3	7
Non-profit	3.3	-
Total	100	100

Productivity: publications

Prior to the award year, Turing scientists published an average of about 28.23 articles (median 22), catalogued in the *Web of Knowledge*.[153] Scientists in the control group had 21.5 publications (with a median of 12, see Table 6.3). The rate of solo publications for both groups was about the same: 35.6 percent for Turing Award scientists and 34.5 percent for the control group (data not shown in the table). The variance in the distribution of the total number of publications was higher for non-Turing

[152] Out of 14 students who published with their advisors, all but two had found first jobs in academia.
[153] See Appendix G on publication practices in computer science.

scientists (s^2= 621.5 versus 369.6 for Turing scientists, not shown in the table). The differences in the publication rate also favored the group of Turing Award scientists who published at a higher rate than the control group (1.22 vs. .84). Thus, compared to the control group, Turing Award scientists, on average, were more productive and had less variation in the number of publications but slightly more in the rate of publications, suggesting differences in publication practices among scientists in their group.

The publication patterns also varied within the disciplines in which scientists were trained (not shown). In the combined group (N=60) of Turing and control group scientists, those with degrees in computer science had an average of 31.94 publications (a median of 22), those in engineering had an average of 27.25 (a median of 11.5), those in mathematics had an average of 22.14 publications (a median of 18), those in physics had an average of 11 publications, (a median of 11), while those in other fields had an average of 20.17 publications (a median of 13). Thus, the publication productivity of scientists trained in computer science appears to be closer to those in engineering and mathematics and higher than that of scientists trained in other disciplines (this pattern may also reflect differences in time because those trained in computer science were younger and were subjected to different publication standards).

Impact: citations

Similarly, Turing scientists received more citations for a single (most cited) publication prior to their award, an average of 198.5 (median 80), while the most cited publication of the control group scientists received an average of 90.87 citations (25.5 median, see Table 6.3).[154] The variance of citations to the most cited publication was higher among Turing scientists (s^2=113,581.64) than among the control group (s^2=31,353.02), suggesting that, although Turing Award scientists were more productive as a group, their most cited publications were not always highly cited.

Eminence: awards

[154] The skewed nature of citations was addressed by a square root transformation. See Chapter 3 on Methods.

Not surprisingly, Turing Award winners were more eminent (prior to receipt of the Turing Award), reporting an average of about 2.23 awards compared to only 0.43 awards reported by non-winners (see Table 6.3). Thus, not counting memberships in National Academy of Science (NAS) and Engineering (NAE), Turing scientists had four times as many awards (51) as control group scientists (12). The majority of these awards came from professional associations while others were fellowships from companies or foundations rewarding creativity, promoting research, or providing time off from teaching and administrative responsibilities. Scientists had to apply for some awards (e.g., a Guggenheim or Fulbright fellowships), while, they had to be nominated, selected or elected by fellow scientists for others (ACM, IEEE, other societies). The election to the National Academies also favored Turing Award winners, twelve (12) whom were elected to the NAE and four (4) to NAS prior to their Turing Award, whereas the control group had only one member of the NAE and no members of NAS. Thus, compared to non-Turing scientists, Turing Award scientists, as a group, were more esteemed and renowned prior to receiving the Turing Award than the control group.[155]

Location: elite organization

At the time of the award, 50% of the winners were employed at top five academic institutions for computer science, while only 13% of the control group scientists were employed in one of these institutions. Although control group scientists had more diverse career paths, many of them worked in academic institutions of lower prestige than the top five academic institutions. Out of 14 Turing and six control group scientists who started their first jobs in an elite institution, six Turing Award winners (43%) were working in the same or similar status institution at the time of the award compared to only one (17%) non-winner (not shown) after equivalent number of years (as the Turing Award scientist).

Number and Type of Collaborators

[155] It is interesting to note the differences in the number of prior awards between early (first 10) and late (last 10) Turing Award winners. Late Turing Award winners have 2.8 times more prior awards (were more eminent) than early Turing Award winners. Longer waiting time for the Turing Award and growing proliferation of awards in general may have contributed to this outcome.

Turing winners had more collaborators than non-winners, an average of 25.7 co-authors (median 23.5), compared to an average of 14.9 co-authors (median 7) for the control group scientists, as shown in Table 6.3. A higher variance for Turing scientists (s^2 =365.75), compared to non-Turing (s^2 =261.36), suggests more variation in the number of collaborators among Turing Award winners, although scientists in both groups had both large and small numbers of collaborators. Turing Award scientists had in total 24 co-authors who already had the Turing Award, and 15 coauthors who were members of the Turing Committee.[156] The control group of scientists, on the other hand, had only nine (9) Turing Award collaborators and two (2) Turing Committee members in their networks of collaborators, which are respectively 2.7 times and 7.5 times fewer than those of Turing Award scientists (see Table 6.3). This reveals compositional differences among collaborators of Turing and control group scientists. The control group scientists had fewer collaborators, including eminent collaborators such as Turing Award winners and Turing Committee members who could sponsor them (support their candidacy) for the Turing Award.

Visibility in the ACM

Almost twice as many Turing Award winners published in ACM journals, compared to the control group scientists (97% versus 57%). Turing winners also received more ACM awards while control group scientists held more service positions in the ACM (compared to winners).[157] The visibility in the ACM score (constructed) confirms that, compared with non-winners, Turing Award winners were more visible in the ACM scientific community through publications and awards.

CORRELATION ANALYSIS

[156] Co-recipients of the Turing Award were not counted as collaborators with the Turing Award. As a matter of interest, 23 co-authors of Turing winners went on to win a Turing Award, suggesting that becoming a Turing Award winner puts one's collaborators "at risk" of winning an award ("consecration," similar to the colleagues of movie stars, see Rossman, Esparza, & Bonacich, 2010).

[157] The data on service positions at the ACM are self-reported and may be incomplete. I did not count membership on the Turing Awards Committee as a service, which by all standards is an important one.

Correlation analysis helps to summarize the relationships among variables by providing information about the extent to which the dependent variable is (linearly) associated with independent variables and the degree to which the independent variables are related. Pearson (point-biserial) correlation coefficients were calculated for a two-category nominal dependent variable (receiving a Turing Award, that is being a *winner* versus *non-winner*) and eight interval independent variables (*publication rate, square root of maximum citations*, *number of prior awards*, *number of coauthors*, *number of coauthors who won the Turing Award*, *number of coauthors members of the Turing Committee, early advantage score*, *visibility in ACM score*; see de Vaus, 2002, pp. 275-276). For two nominal variables—*being a winner/non-winner* and *employment in an elite organization*—I provided other measures of association: Phi coefficient, Lambda and Goodman and Kruskal tau coefficients. The results, displayed in Table 6.5, indicate a particularly *strong* (r above .5) and statistically significant relationship between a) the maximum number of citations and the number of co-authors, r (58)=.564, p=<0.001; b) being a winner and having received prior awards, r (58)=.521, p=<0.001; c) the number of co-authors and number of co-authors who already won a Turing Award, r (58)=.574, p=<0.001; and between d) the publication rate and the number of co-authors, r (58)=.503, p=<0.001.

In addition, Table 6.5 reveals a *substantial* (r between 0.40 and 0.50) relationship between a) having coauthors who won the Turing award and coauthors who are members of the Turing Committee, r (58)=.495, p=<.001; b) being employed in an elite institution and having coauthors who won the Turing Award, r (58)=.467, p=<0.001; c) the ACM visibility score and the number of awards, r (58)=.453, p=<0.001; d) being employed in a elite organization and having co-authors who are members of the Turing Award Committee, r (58)=.432, p=<0.01; and e) having received an early advantage and having coauthors already Turing Award winners,

Table 6.5. Pairwise Correlations Among Variables

	Winner	Pub Rate	Max Citation (sqrt)	Co-authors	Co-authors Already Turing Winners	Co-authors Members of the Turing Committee	Early Adv	Visibility in ACM	Awards	Elite Org
Winner	1	.179	.228	.296*	.240	.272*	.388**	.355**	.521***	.394**
Publication Rate		1	.202	.503***	.193	-.006[158]	.122	.107	.128	.168
Max Citation (sqrt)			1	.564***	.386**	.092	.300*	.161	.201	.161
Co-authors				1	.574***	.344**	.249	.353**	.371**	.369**
Co-authors Already Turing Winners					1	.495***	.424**	.104	.056	.467***
Co-authors Members of the Turing Committee						1	.237	.040	.077	.432**
Early Advantage							1	.122	.126	.135
Visibility in ACM								1	.453***	.208
Awards									1	.076
Elite Org										1

Note: The correlation between two nominal variables, being a winner and being in an elite organization at the time of the award, is as follows: Phi=.394; p<.01, Lambda=.367, p<.01; Goodman and Kruskall's tau=0.155, p<.01 approximately. The stars in the table represent significance levels *p<.05, **p<.01, ***p<.001 (two-tailed tests).

r (58)=.424, p=<0.01. The correlations among variables described above lend additional validity to using these variables as predictors for Turing Award recipients.

The correlation between being a winner and having prior awards is expected since eminent scientists are likely to accumulate more recognition, as predicted by the Matthew's Effect. The finding that the number of coauthors correlates with the publication rate and the number of citations is understandable since the larger network of coauthors indicates high collaboration activities that resulted in publications and, possibly, citations. The strong association between visibility in the ACM and number of awards indicates that those with awards were also likely to have published in ACM journals (as many winners did), as seen in descriptive statistics.[159] The correlation between the total number of coauthors and coauthors who already were Turing Award

[158] The negative sign of the coauthors members of the Turing Committee variable may be a side effect of multicollinearity—high correlation among collaborative variables and their conceptual relation to publication and citation measures. Multicollinearity is addressed on the next two pages.

[159] Part of the correlation is also due to the fact that those with awards (mostly winners) were more likely to have had ACM awards (n=10).

winners implies that those who have large networks are also more likely to have collaborators who had already won the Turing Award (possibly describing a position of stature). This description fits Turing Award winners and their collaborative patterns, compared to the control group (see Table 6.3 and next paragraph). The correlation between the variables representing collaborators with a Turing Award and collaborators who were members of the Turing Committee (among winners and non-winners combined) is subtle and raises questions about the collaborative networks of scientists who have Turing Award winners and Turing Committee members among their collaborators. What is the basis of their relationship? Were they affiliated with the same institution? The data collected cannot answer these questions; however, having such colleagues among decision-makers was clearly beneficial. Being part of the Turing Committee meant that these collaborators could testify to the contribution and quality of work of Turing scientists.

The substantial strength of correlations among a set of variables— having 1) coauthors with a Turing Award, 2) coauthors who were members of the Turing committee, and 3) being employed in elite organizations— suggest attributes of a privileged position which entails being in an elite institution and having resourceful coauthors (social capital). The relationship among highly correlated variables (e.g., collaborative variables) also raises concerns about multicollinearity.

Multicollinearity (strong correlation among independent variables) results from inclusion of "highly related" independent variables, particularly of the same or similar constructs, in the same regression model (Cohen et al., 2003, p. 420). Because multicollinearity can lead to unstable regression coefficients associated with large standard errors that could complicate their interpretation (Cohen et al., 2003, pp. 420-425), it was carefully examined. Multicollinearity diagnostics (variable inflation factor [VFI] and tolerance measures) were obtained from a multiple regression procedure. The variance inflation factor (VIF) for independent variables in the regression is a common measure of multicollinearity as it "provides an index of the amount that the variance of each regression coefficient is increased relative to a situation in which all of the predictor variables are uncorrelated" (Cohen et al., 2003, p. 423). The computed VIF measures were far below the rule of thumb of 10 for VIF (and tolerance less then .10). However, the variables with the highest VIF measures—the number of coauthors (VIF=3.258, tolerance =.307) and coauthors already Turing Award winners (VIF=2.247, tolerance=.445)—raised some concern of being potentially problematic. Although all three collaborator variables measure different aspects of collaborations, they might be related (being attributes of a privileged position). The decision was made to identify and use the best predictor among the three collaborator variables in order to reduce multicollinearity related to collaborator variables.[160]

The correlation among a constellation of variables (having early advantages, employment in an elite organization, coauthors with a Turing Award, coauthor members of the Turing Committee, publication rate and citations) strongly suggests that they all represent attributes of an elite status position[161] (Turing and control groups overall differ on these variables). Such status position may render some of the variables used as redundant (since they are attributes of a status) raising concerns for multicolinearity and confounding variables. To reduce (but not to eliminate) the effect of confounding variables, I took the following measures: 1) variables were chosen with care to reduce the overlap, 2) alternative explanations were considered and incorporated into regression models (Frank, 2000), and 3) variables were ordered according to causal priority (Cohen et al., 2003). Since none of the other variables tested positive for mutlicollinearity or interaction, no other adjustments were necessary.

LOGISTIC REGRESSION ANALYSIS

The logistic regression procedure allows one to assess the predictive value—the effect of independent variables upon the likelihood of receiving a Turing Award. The coefficients (*B*) from a logistic regression equation are interpreted as the change in the

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[160] An alternative would have been to construct an index variable from the three collaborator variables which would have undermined the original purpose of inquiry to differentiate between these three variables.

[161] The elite status can be summarized as follows: starting with early advantages, being employed by an elite institution, having a large number of coauthors, coauthors with a Turing Award and/or Turing Committee members, and having higher numbers of publications and citations.

log odds (logit) of a response per unit of change in the predictor variable while *odds ratio*, representing exponentiated coefficient (e^B), shows "by what amount the odds of being in the case group are multiplied when the predictor is incremented by a value of one unit" (Cohen et al., 2003).

As indicated in chapter 1 and described in chapter 3, I will consider five logistic regression models. *Model 1* includes only productivity and impact measures: publication rate and maximum citation to a single publication. *Model 2* adds the collaborator variables and identifies the strongest predictor that is then added to the combination of other predictors in *Model 3* ("standard model"). In *Model 4*, I add a new variable—awards and in *Model 5*, in addition to awards, I will consider employment in the elite (top five) academic institutions for computer science. The results of logistic regressions appear in Tables 6.6 and 6.7.

Model 1 includes the most essential variables likely to contribute to chances of receiving the Turing Award: publication rate and the impact of most cited publication. *Model 2* explores the effect of collaborators—number of coauthors, coauthors who already won the Turing Award, and coauthors who were members of the Turing Committee. The effectiveness of variables is assessed using Wald statistic. If Wald statistic is significant (less than .05), I reject the null hypothesis that the variable does not make a significant contribution to the outcome. I report the results in terms of odd ratios that indicate the relative amount by which the outcome is likely to change when the independent variable increases by one unit.

The regression results for *Model 1* (see Table 6.6) indicate that we cannot reject the null hypothesis of no effect of publication rate and maximum citation—that is, the data do not provide enough evidence to distinguish between winners and non-winners based on these variables (based on Wald statistic). Nonetheless, it is noteworthy that with each additional unit increment in publication rate (one publication per each year of work history), the odds of receiving the award increase by 32%, holding other variables constant. Likewise, the variables in *Model 2* have no significant effect for distinguishing between the groups of winners and non-winners. However, among collaborative variables, the contribution of the coauthors who were members of the Turing Committee to winning the Turing Award is more substantial than the contribution of other collaborative variables. With each additional coauthor who is a member of the Turing Committee, the odds of being a Turing Award winner increase by a factor of 2.5, holding all other variables constant.

Table 6.6. Results of Logistic Regression for Models 1 and 2: Turing Award (N=30) and Control Group Scientists (N=30), 1966-2008

	Model 1 (Basic Model)			**Model 2** (Basic with Collaborative Variables)		
Independent Variable	Coefficient	S.E.	Odds Ratio	Coefficient	S.E.	Odds Ratio
Constant	-.810	.482	.445	-.978	.500	.376
Publication Rate	.277	.266	1.320	.237	.308	1.268
Max Citation (sqrt)	.059	.041	1.061	.042	.047	1.043
Co-authors				.008	.024	1.008
Co-authors Already Turing winners				.002	.402	1.002
Co-authors Members of the Turing Committee				.930	.686	2.534
Model Evaluation						
-2 Log likelihood	78.720			73.780		
Model χ^2	4.458			9.398		
Hosmer and Lemeshow χ^2 (df=8)	12.444			14.486		
Cox and Snell R^2	.072			.145		
Nagelkerke R^2	.095			.193		
P.C.P. (proportion of cases correctly predicted)	58.3%			55%		
N	60			60		

**p*<.05 ***p*<.01 ****p*<.001 (two-tailed tests)

However, the *p* value is not statistically significant. The other two variables, the number of coauthors and co-authors Turing Award winners, have almost no effect on the outcome; their regression coefficients are close to zero (and odds ratio is close to 1). Since coauthors and coauthors Turing Award winners have so little contribution and the model itself is not predictive, multicollinearity is less of a concern. Thus, I conclude that the best collaborator variable is *coauthors who are members of the Turing Committee*, and I shall use it for other analyses.

The next three models, *Model 3*, *4* and *5*, displayed in Table 6.7, assess the contribution of additional factors to the probability of receiving the Turing Award.

Model 3, the standard model, adds an early career advantage score and visibility in ACM score. While all the variables are positively associated with being a winner, the odds ratio is the greatest for an early advantage score and visibility in ACM. More specifically, with each one unit increase in early advantage and visibility score, the odds

Table 6.7. Results of Logistic Regression for Models 3, 4 and 5: Turing Award and Control Group of Scientists, 1966-2008

	Model 3 (Standard Model)			**Model 4** (with Awards)			**Model 5** (with Elite Org)		
Independent Variable	Coeffi-cient	S.E.	Odds Ratio	Coeffi-cient	S.E.	Odds Ratio	Coeffi-cient	S.E.	Odds Ratio
Constant	-2.210	.734	.110	-2.208	.783	.110	-2.634	.884	.072
Publication Rate	.250	.304	1.284	.083	.336	1.086	.015	.352	1.015
Max Citation (sqrt)	.024	.045	1.024	.006	.047	1.006	.004	.049	1.004
Co-authors Members of the Turing Committee	.724	.578	2.062	.840	.744	2.317	.491	.929	1.633
Early Advantage	.985*	.489	2.677	.883	.519	2.418	1.064	.570	2.899
Visibility in ACM	.955*	.441	2.599	.349	.519	1.418	.125	.562	1.133
Awards				.859*	.331	2.360	.963**	.361	2.620
Elite Organization							2.020*	.888	7.542
Model Evaluation									
-2 Log Likelihood	63.289			52.448			46.661		
Model χ^2	19.889**			30.730***			36.517***		
Hosmer and Lemeshow χ^2	14.642			10.733			8.568		
Cox and Snell R^2	.282			.401			.456		
Nagelkerke R^2	.376			.534			.608		
P.C.P. (proportion of cases correctly predicted)	71.7%			81.7%			86.7%		
N	60			60			60		

*p<.05 **p<.01 ***p<.001 (two-tailed tests)

of receiving the award increase by a factor of 2.7 and 2.6 respectively. Further, with each additional coauthor Turing Committee member, the odds of receiving the award increase by a factor of about 2.1. With each additional unit increment in publication rate (one publication per each year of work history), the odds of receiving the award are multiplied by 1.28, holding other variables constant. The increase in odds of being a winner with each unit increase in (square root of) citations was surprisingly minor (2.4%), given the magnitude of differences in citations encoded by square root transformation

($\sqrt{64} = 8,\ \sqrt{16} = 4$ and the difference in square roots is 4 while the difference between having 64 and 16 publications is 48).

Model 4 adds another important variable, the number of previous awards. Each additional award increases the odds of being a Turing Award winner by a factor of 2.4 (p<.05), almost the same amount as having an early advantage or an additional coauthor who was a member of the Turing Committee. The addition of awards only slightly changes the contributions of other variables, except for visibility in the ACM, which loses almost half of its predictive power. Having early advantages still substantially contributes to the odds of being a Turing Award winner (by a factor of 2.4). Finally, *Model 5* introduces employment in an elite organization. Again, in this model, all variables positively contribute to the outcome, and two variables have particularly strong and significant predictive effects: prior awards and employment in an elite organization. Having a prior award increases the odds of receiving a Turing Award by a factor of 2.6 (p<.01) while for those employed in top five universities for computer science, the odds of being a winner are 7.5 times higher (p<.05), holding other variables constant. *Model 5* is most effective in accounting for the outcome, based on the models' goodness of fit measures provided in Table 6.7.[162]

QCA ANALYSES

I use qualitative comparative analysis (QCA) of cases to compensate for some of the limitations of the quantitative approach, and in particular, a conservative bias that discourages interpretive analysis of cases and limits the understanding of events/factors affecting scientific careers (see Ragin, 1987). QCA provides a way of exploring cases

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[162] Although the focus of regression models has been on testing independent variables, Tables 6.6 and 6.7 provide summaries of model fit. Model Chi-square for the last three models is statistically significant, indicating that predictors have an effect on the dependent variable (rejecting the null hypothesis that independent variables have no effect on the dependent variable). Also -2 log likelihood measures (testing model capability of predicting the observed values from the independent variables) improved from Model 3 to 4 (by 10) and from Model 4 to Model 5 (by 5). The Hosmer and Lemeshow test (its non significance) indicates that the predictions of Models 3, 4 and 5 do not significantly differ from the observed values, thus implying a good fit.

holistically[163] and testing alternative explanations for the outcome of winning or not. Since qualitative comparative analysis uses Boolean algebra, I reduced[164] seven original career dimensions to six and re-interpreted them in Boolean terms for the presence (1) or the absence (0) of career attributes: an early career advantage, high impact publication, awards, coauthors sponsors, publications in ACM journals, and employment in a top research university at the time of the award. Some of the interval variables had to be split into two categories: 1) high or low impact of publications, measured by citations, was created based on the combined median of Turing and control group scientists' citation counts (above median[165] was coded as 1 and below was coded as 0); and 2) high (coded as 1) or low (coded as 0) eminence, measured by prior awards, was based on having at least one award (above 1 was coded as 1, below as 0).

QCA analysis proceeds by constructing a truth table[166] with $2^6=64$ rows (where 2 represents two possible states of events 0 or 1) accounting for all possible combinations of six conditions and assessing the actual frequency (the number of instances) of their occurrence. Table 6.8 lists the most frequent combinations with three or more occurrences and corresponding coding in relation to the outcome that were used for the next steps of analysis.

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[163] The case-oriented approach is holistic to the extent that it treats and compares cases "as whole entities and not as collections of parts" (Ragin, 1987, pp. ix-x). The attention to complexity ("heterogeneity and particularity of individual cases") is a distinguishing feature of qualitative approaches (Ragin, 1987, p. xii). Cases may vary with regard to the combination of operating conditions, their order, and their meaning. The qualitative comparative analysis allows one to investigate the diversity of individual case and consider the intersection of combination of conditions, different empirical processes, and causal mechanisms (complexity) leading to the outcome.

[164] The selection was guided by confidence in a particular variable. I decided to leave out the publication statistic since it only represented peer reviewed publications and did not consider books and conference proceedings.

[165] I used median values, as opposed to average values, because of the skewed nature of citations.

[166] The truth table, as used in logic and Boolean algebra, is a table with all possible combinations of variables and the outcome rendering the expression (row of the table) as true or false. In the table, data are represented in binary form (as 1 for the presence of a condition [true], and as 0 for absence [false]). In QCA, each row of the table represents a combination of values of the independent variables and the outcome. Cases are then sorted, and only the most frequent cases are retained and simplified to the logically minimal solution.

Table 6.8. QCA, The Most Frequent Combinations of the Six Conditions (1=yes, 0=no)

Early Advantage	High Citations	Awards	Sponsors	Publications in ACM	Elite Organization	Frequency	Outcome (Turing Award)
1	1	1	1	1	1	7	1
0	0	0	0	0	0	6	0
0	0	0	0	1	0	5	0
1	0	1	0	1	0	4	1
1	1	1	0	1	0	4	1
0	1	1	0	1	1	3	1

The fsQCA software, generously provided by Charles Ragin on his website,[167] helped to simplify[168] the number of conditions and "derive a logically minimal equation" describing those conditions and the associated outcome using the rules of Boolean algebra (Ragin, 1987, p. 98). The software produced two results: 1) a complex solution, describing all of the most frequently occurring cases, and 2) a parsimonious solution, the result of extreme minimization of conditions accounting for the outcome of receiving a Turing Award.

Table 6.9 presents complex solution listing the three most frequent career combinations associated with winning the Turing Award. The first combination describes those scientists (20%) whose career achievements contained nearly all of the crucial variables: 1) early advantages (*eadv*) (fellowships, publications with advisor, first jobs in top five programs), 2) higher cited publications compared to peers in the group (*highcites*), 3) eminence (*awards*), 4) publications in ACM journals (*pubsacm*), 5) sponsors (Turing Award winners or Turing Committee members) among collaborators, and 6) affiliation with an elite university at the time of the award (*eliteorg*). The second combination describes scientists (10%) who were working in elite universities, published in ACM journals, had high citations, and awards, but did not start with early career

[167] See http://www.u.arizona.edu/~cragin/fsQCA/software.shtml
[168] "If two Boolean expressions differ in only one causal condition yet produce the same outcome, then the causal condition that distinguishes the two expressions can be considered irrelevant and can be removed to create a simpler, combined expression" (Ragin, 1987, p. 93).

advantages and had no sponsors among collaborators. The third combination describes those (23%) who did not end up in elite universities and did not have coauthors who could sponsor them for the award but who published in ACM journals and had received prior awards; interestingly, they also started with early career advantages. These three career profiles have high consistency (above 0.85, see Table 6.9). Although they account for only 53% of all cases, they represent the *dominant career profiles of Turing winners* in these career dimensions.

Table 6.9. QCA Complex Solution Explaining Winning Outcome

Combination of Conditions	**Raw coverage**	**Unique coverage**	**Consistency**
1. eadv*highcites*awards*sponsors*pubsacm*eliteorg	0.200000	0.200000	0.857143
2. ~eadv*highcites*awards*~sponsors*pubsacm*eliteorg	0.100000	0.100000	1.000000
3. eadv*awards*~sponsors*pubsacm*~eliteorg	0.233333	0.233333	0.875000

Note: Frequency cutoff = 3, consistency cutoff = 0.75, solution coverage = 0.53, solution consistency = 0.89.

Consistency is “the proportion of cases in a given row that displays the outcome in question” (Ragin, 2008, p. 27). A value close to 1 indicates high consistency, while less then that indicates differences among cases that share these conditions in respect to the outcome. *Solution coverage* measures “the proportion of memberships in the outcome that is explained by the complete solution” and *raw coverage* measures “the proportion of memberships in the outcome explained by each term of the solution” (Ragin, 2004, p. 86). The *unique coverage* measures the uniqueness of solution if there is overlap (there is none in this case).

The complex solution can be examined further for necessary and sufficient conditions (causes). A cause is *necessary* if “it must be present for an outcome to occur,” and a cause is *sufficient* “if by itself it can produce a certain outcome” (Ragin, 2008, p. 42). Upon a close examination of the complex solution, two conditions—awards, and publications in ACM journals—emerge as *necessary* (must be present) but *not sufficient* by themselves to lead to recognition with a Turing Award.

A parsimonious solution (produced by software) with the most essential conditions to distinguish the cases is listed in Table 6.10. This solution reduced all of the factors to only one: *awards*, which accounts for 80% of all cases with a respectable degree of consistency (.73). Thus, the membership in the set of Turing Award winners can be determined largely by having prior awards.

Table 6.10. QCA Parsimonious Solution Explaining Winning Outcome

Combination of Conditions	Raw coverage	Unique coverage	Consistency
Awards	0.800000	0.800000	0.727273

Note: Frequency cutoff = 3, consistency cutoff = 0.75, solution coverage = 0.80, solution consistency = 0.73.

Comparison with Logistic Regression[169]

The logistic regression assessed the contribution of each variable to distinguishing winners from non-winners and helped to identify the strongest variables associated with being a winner: namely, location in an elite organization, awards, having an early advantage, and visibility in ACM. The results of regression analyses accentuated the characteristics associated with careers of Turing Award winners and described winners (and non-winners) as a group. QCA analysis, on the other hand, identifies subgroups among winners and the conditions/pathways describing their careers. Specifically, QCA helped to identify three dominant profiles of Turing Award scientists: those employed in elite organizations, eminent and highly cited, and two other subsets of winners. The one subset is composed of mavericks who started with early career advantages but whose career accomplishments did not include working in an elite university or having certain types of coauthors—potential sponsors (however, it did include publications in ACM and awards). The other subset is composed of those who did not start with career advantages but who, nevertheless, became accomplished (with high citations and awards) and visible researchers, and who won the Turing Award, despite their lack of sponsors-collaborators. In future investigations, QCA would be a helpful tool in refining and capturing the attributes of diverse career paths leading to recognition by the Turing Award. QCA requires fine-tuning and balancing solution coverage (that is, the number of cases that can

[169] A mixed method approach used in this study, involving the use of logistic regression and a Boolean analysis, was undertaken by Ragin, Mayers and Drass (1984) with a successful outcome of finding a pattern of inequality missed by the quantitative “global assessment.” They recommended the use of the Boolean method in combination with statistical analyses to identify “descriptively meaningful” and subtle patterns.

be explained by particular combinations) and solution consistency (that is, the consistency of the solution across all known cases) in accounting for accuracy of outcomes. This is challenging to accomplish in highly heterogeneous groups such as computer professionals.

DISCUSSION AND CONCLUSION

This study began with a set of hypotheses aimed at understanding the differences between Turing Award winners and control group of non-winners, and explaining the career outcome of winning. The basic logistic *Model 1* with most essential information in nominations and evaluations—publications and their impact—could not account for the outcome. Further, since the differences in composition and utility of collaborators for winning were not clear at the beginning of the study, I decided to empirically test and select the best collaborative variable. Using *Model 2*, and including the same essential variables of *Model 1* plus collaborative variables, I was able to compare the effect of three related collaborative variables: number of collaborators, presence of coauthors already Turing Award winners, and members of the Turing Committee. The effect of having Turing Committee members among collaborators was most substantial, and this variable was chosen for the subsequent set of comparisons in which my hypotheses were tested.

In *H1*, I expected Turing Award scientists to have publication productivity superior to that of the control group. The descriptive statistics supported this proposition—Turing scientists had slightly higher publication rates. However, despite having a substantially large (35%) contribution to the odds of being an award winner in *Model 1*, publication rate was a weak predictive variable in other regression models (thus, only partially supporting the hypothesis).[170] In *H2*, I expected that the contributions of

[170] In the Appendix G, I address publication practices in computing: the prevalence of publishing in conference proceedings and problems associated with using publication rates solely based on refereed articles, making it an incomplete measure of productivity. Measures of scientific productivity often do not include books. I experimented with including a count of books published prior to prize year (retrieved from WorldCat OCLC [Online Computer Library Catalog] database) into the measure of productivity. Turing Award winners as a group published more (33) books than the control group (22). Counting books (1 book

Turing Award winners, compared to non-winners, had a stronger impact (measured by the number of citations to the most-cited article prior to the Turing Award) in the scientific community and, as a result, on their receiving the award. Whereas descriptive statistics provided evidence in favor of this hypothesis (*H2*) and citations had a positive impact on the outcome in regression analyses in *Models 1* through *5*, the impact of contributions (citations) was not at all effective at differentiating winners from non-winners (thus only partially supporting *H2*).[171] In *H4*, I hypothesized that early career advantages may become crucial for later career outcomes such as the receipts of the Turing Award. *Model 3* supported this hypothesis while the other two models (4-5) only partially supported it (i.e., positively associated, high impact but not statistically significant). In *H5*, I expected Turing Award winners to have greater eminence (i.e., receive a substantially higher number of awards than the control group), and in *H6* I hypothesized that they would be employed in top computer science universities. *Models 4* and *5* supported the hypothesis for awards (*H5*) and *Model 5* supported the hypothesis for employment in elite universities (*H6*). In fact, these two variables were the strongest (and statistically significant) predictors of receiving the Turing Award, thus suggesting for winners the operation of the Matthew Effect ("accruing of greater increments of recognition for particular scientific contributions to scientists of considerate repute and the withholding of such recognition from scientists who have not yet made their mark" [Merton, 1968/1973, p. 446]).

In *H3b*, I posited that, compared to non-winners, the collaborators (social capital) of Turing Award scientists would be compositionally different and potentially more instrumental for recognition. Not only were Turing Award scientists more likely to have Turing Award winners as co-authors, they also had coauthors who were members of the Turing Committee. Both types of collaborators could have served as "reputational

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= 4 articles) together with articles as part of the publication rate increased the contribution of the publication rate variable to the odds of receiving the Turing Award by about 11% on average (e.g., in Model 3 from 28.4% to 37.3%, in Model 4 from 8.6% to 18.9%, and in Model 5 from 1.5% it went to 16.2%).

[171] This finding should be interpreted with caution, for the impact of one's contribution may not be captured by the number of citations.

entrepreneurs" – those with motivation and institutional position to create a reputation/image for a nominee (Fine, 1996). Indeed, the presence of the Turing Committee members among coauthors was associated with being a winner (*Models 2-5*), supporting my hypothesis (*H3b*). Finally, in *H7*, I hypothesized that, compared to non-winners, Turing Award winners would be more visible to the awarding organization (ACM). Regression *Model 3* supported the hypothesis. In the absence of information on prior awards and employment in an elite university, visibility in the ACM was a good predictor of recognition with the Turing Award; however, the effect was weaker in the presence of awards and elite organization variables (*Model 4* and *5*). To conclude, the regression analyses helped to identify the optimal (and statistically significant) variables associated with being a winner: namely, *visibility in ACM, early advantage,* prior eminence (*awards)* and *location in elite organization* (*Model 3, 4* and *5*). The effect of having collaborators who were members of the Turing Committee was also substantial but not statistically significant.

The career factors associated with "becoming eminent—a Turing Award winner" can be summarized (considering the results of the t-test for equality of means) as having **more**: 1) *early career advantages* (specifically, first jobs in top five programs); 2) *prior eminence* (awards); 3) employment at *top/elite universities* at the time of the award; 4) larger *number of collaborators* and *collaborators who had experience as members of the Turing Committee*; and 5) *visibility in ACM*. Some differences also appear with regard to: 1) *citations*; 2) *publications* (rate); and 3) the presence of *co-authors already Turing Award winners*. However, the contribution of these variables to the likelihood of being a winner was much smaller than that of other variables. The findings thus suggest that although Turing Award scientists had more distinguished professional status overall (especially in terms of visibility, institutional location, type of collaborators, and prior level of recognition), the impact and merits of their contributions were not evident. I will examine in more detail three major differences between Turing Award winners and the control group— in eminence, collaborators, and organizations.

Eminence

The findings (logistic *Model 4* and *5*) provide evidence that winning a Turing Award is strongly associated with a prior record of recognized success. The pattern of rewarding those with prior awards and achievements acknowledges already recognized contributions and may represent a risk aversive organizational strategy. By awarding already esteemed scientists and engineers, the Association for Computing Machinery reduces the organizational risk and uncertainty of recognizing unknown or potentially questionable contributions of candidates without attributes of honor (awards, employment in elite universities). Though ACM accepts nominations from the wider community of computer scientists, it is not known whether candidates with no awards or from less prestigious organizations are nominated and if they receive serious consideration.

Collaborators

The findings point to the substantial differences in collaborators (co-authors) of winners compared to non-winners. The non-winners had far fewer collaborators and their collaborators were less likely to be Turing Award winners or Turing Committee members. Given the small effect of the number of collaborators on the outcome of receiving the Turing Award, it was not the *number* but the *type of collaborators*, particularly of Turing Committee members, that differentiated Turing Award winners from non-winners. To account for collaborative differences, I offer two explanations that were likely to operate in combination.

First, collaborators are well positioned to nominate and/or select a coauthor because they share a problem area (and thus form an "invisible college" [Price, 1963]) and a sense of importance and value of particular research. Collaborative ties are consequential because they may function as a "moral economy" [172] of science (Daston, 1995; Shapin, 1994), especially in the early history of computer science. Additionally,

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[172] Moral economy is "a web of affect-saturated values that stand and function in a well-defined relationship with one another" (Daston, 1995, pp. 4-5). Daston (1995) argued that moral economies are "integral to science: to its sources of inspiration, its choice of subject matter and procedures, its sifting of evidence, and its standards of explanation" (p. 6).

having collaborators is important for communicating state-of-the-art research: "The communication network linking the inner circle of the scientific elite generally ensures their knowing about 'interesting work' going forward in their field" (Zuckerman, 1977, p. 178). Moral bonds of trust that foment collaboration are likely to form among groups of scientists and these bonds may become morally consequential. Thus, nominating and/or selecting a fellow colleague is a rational decision because it is both the result of knowledge about an area with which one is most familiar and a moral obligation in which one promotes and recognizes the achievements of a scientist in his or her research area.

Second, to assert their values, the collaborators had to have decision-making power in the award process. Thus, it is unsurprising that having collaborators who were Turing Award Committee members was associated with receiving the prize. After all, members of the Turing Committee were the ones making the final decision. A clue about the importance of committee members and influence of former winners on the committee decisions was noted also in the study of Nobel laureates. Accounting for more than half of American laureates having been apprentices to other laureates, Zuckerman suggested that there "must be something about the process of selecting Nobel laureates" (1977, p. 106). From chapter 4, we learned that some Turing Award scientists later became members of the Turing Award Committee, so we should not be too surprised to find their "Turing class" collaborators among the winners of the Turing Award. The archival documents provided evidence that collaborators of the control group scientists were not part of the Turing Committee, thus disadvantaging them in the selection process.

Organizations

The sectors and organizations in which Turing Award and matched scientists worked revealed little differences in distribution of scientists of either group *between* sectors, but more substantial differences *within* sectors in terms of prestige and visibility of organizations. Turing and control group scientists mostly worked in both academia and industry (90 percent of their work histories). In academia, Turing Award winners, compared to non-winners, were more likely to work in prestigious universities (during the first job: 47% vs. 20%; in the entire career: 77% vs. 40%; at the time of the award 50% vs. 13%). Furthermore, non-Turing scientists were more likely to work in laboratories, and Turing scientists, when employed in industry, were more likely to work for IBM. An affiliation with IBM, which was highly visible and dominant in the computer industry in the second half of the 20th century, was conducive to recognition. The experience of non-Turing scientists with self-employment and their association with laboratory work may suggest higher autonomy and control in the workplace that may also have resulted in a greater degree of isolation leading to their diminished centrality and visibility in research. Thus, I conclude that some work settings (laboratories, small firms, self-employment) provide less visibility to the scientific community and consequently decrease one's chances of being recognized with a Turing Award.

A strong correlation between working in a prestigious institution and having collaborators who are already Turing Award winners as well as having collaborators who served at some point on the Turing Committee requires an explanation. The correlation suggests a connection between job locations and the type of collaborators one may have—being located in an elite institution is associated with having more distinguished (Turing Award winners) and more resourceful (Turing Committee members) collaborators. This pattern describes Turing Award winners. In fact, scientists seeking superior research environments often do not have to choose between 1) prestige and 2) a high quality research environment (resources, values, and esteemed colleagues) as the two have been noted "to go hand in hand" (Zuckerman, 1977, p. 156). Whereas the record of publications and citations did not distinguish Turing Award winners from non-winners, the differences in types of collaborators were more salient. Turing Award winners had more Turing Committee members and other Turing Award winners among their collaborators—the types of collaborators who were well positioned to promote Turing scientists for the award. Turing winners also benefited from the "halo" effect of their prestigious universities (Crane, 1965). These two advantages tend to go together: elite universities provide access to eminent (award-winning) and "resourceful" colleagues (Turing Committee members) who, in turn, provide greater visibility of fellow scientists and their research to the computing community at large.

The distinguished status of Turing Award winners at the time of nomination raises a concern of whether the prestige and ranking of the institutions for which they worked had any influence on award evaluators. Researchers have noted a social propensity to acknowledge worth, dignity, superiority, or prestige [of titles, institutions] (Shils, 1968; Wegener, 1991); and that in the absence of information about merit, "people [tend to] rely on the 'judgment of others,' often coded in markers such as medals, a university degree, etc" (Henrich & Gil-White, 2001). Thus, committee members evaluating candidates with more honors and prestigious departmental locations can more easily construct the worth (and, perhaps, entitlement) of those candidates based on the prestige of candidate's degrees, awards, and associations.

Although this study was not designed to specifically address whether recognition by the Turing Award is due to merit or to location in an elite university, the results of regression analyses provided little support for merit measured by citations and signifying the impact and usefulness of contribution, or by publication rate, indicating researcher's productivity and contribution. In fact, the early career advantage score, with its substantial multiplicative factor, suggests that sponsored mobility (recognition of talent and access to resources such as prestigious jobs and collaborators prior to evidence of productivity) was more likely to occur and to be more consequential. Prior studies have shown that recruitment in prestigious departments was often independent of prior productivity but later productivity conformed to (high) departmental expectations (Allison & Long, 1990; Long, 1978; Long & McGinnis, 1981).

To summarize, the findings presented in this chapter identified four factors that are most strongly associated with winning the Turing Award: 1) early career advantages, 2) professional visibility in the ACM, 3) prior awards, and 4) affiliations with prestigious institutions. Early career advantages such as fellowships, publications with advisors, and first jobs in top research institutions attest to the benefits of getting a head start and being identified early on as "meritorious" (see Zuckerman, 1977, p.61). These advantages were likely to have opened access to resources and means for further occupational achievement. Later achievements were noticed and rewarded as evidenced by awards and positions at prestigious institutions. Surprisingly, the outstanding characteristics of achievements of winners were not conveyed by productivity and citation measures (they were not effective predictors of being a Turing Award winner) but by awards. Turing winners had four to five times as many awards and honors than non-winners. Further, having prior awards proved to be the most essential characteristic distinguishing winners and non-winners in QCA analyses. These findings attest to the operation of two processes of allocation (Merton, 1968/1973, p. 446; Zuckerman, 1977, pp. 59-63) in careers of Turing Award winners: 1) the possible accumulation of advantage in the form of early honors and resources that were subsequently transformed into more achievements; and 2) the possible operation of the Matthew Effect in the distribution of awards— intentional or unintentional bestowal of the Turing Award to already recognized (by awards) scientists which further enhanced their position. The significance of these findings for the understanding of scientific careers and recognition is that in the absence of clear description and markers of achievement, significant awards such as the Turing Awards in computing seem to augment the existing inequalities among scientists. In the concluding chapter, I will summarize these and other results and consider their implications.

CHAPTER 7

CONCLUSIONS

SUMMARY

I began this study by asking two key questions:

1) *Award-Winning Contributions*: What are the valued characteristics of award-winning contributions to computing and the method of selection of these contributions used by the Turing Committee deciding on the award?

2) *Education and Careers of Winners*: Which factors (educational and career-related, including collaboration) are associated with winners of the Turing Award and differentiate them from the control group of non-winning computer scientists?

Question 1

The following findings emerged regarding the valued characteristics of contributions:

a) Over the years, the Turing Committee has made an effort to recognize contributions from a variety of sub-fields in the newly emerged area of computing (the "breadth" criteria). Nevertheless, the majority (60%) of valued (recognized) contributions fell into two categories: Software and Theory of Computation (chapter 4*: Award-Winning Contributions)*. The dominant sub-areas of contributions were Programming Languages and Analysis of Algorithms and Problem Complexity, followed by Programming Techniques and Artificial Intelligence. In regard to the type of contributions (reflected by what the winner actually did), the committee valued (recognized) outstanding publications (7.9% of references in award citations were to publications), contributions to theory and research (32.7% of references in award citations were to theory and research)—broadly fitting into the realm of science, and contributions to practice and design (42.6% of references in award citations were to practice and design activities, combined)—representing work in the realm of technology. Thus, among a broad range of contributions, mainly those in the areas of Software and

Theory of Computation, representing *practice* and *theory*, came to define the core of contributions in computing recognized by the Turing Committee. In addition, the types of contributions referenced in award citations also revealed a "practice" category attesting to a large share of "technological" knowledge in computer science where engineering and science were inextricably bound together.

b) In assessing the contributions of "lasting and major technical importance"—which is the only description of the award—the committee placed importance on the impact and significance of contributions. However, when evaluating the impact and significance of contributions, the committee stumbled over the meaning of "technical," which was interpreted along two seemingly irreconcilable[173] standards of "usability," embraced by industry (associated with "applied research"), and "depth," embraced by academia (associated with "basic research) (chapter 4*: Award-Winning Contributions)*. This conflict of values demonstrates that the award has brought together fragmented sites of knowledge production in computing—academia and industry—despite their different views on what constituted an achievement in computing (see chapter 4*: Award-Winning Contributions* and Chapter 2: *Formation, History, and Nature of the Field of Computing).*

c) Archival records related to the evaluation process revealed that the criteria used to evaluate Turing Award winners were vague (i.e., not clearly stated or specified for the benefit of being "inclusive"), and the emphasis varied over time and under various committee chairs (chapter 4*: Award-Winning Contributions).* The committee asked nominators to specify a single contribution, but allowed multiple and life-long contributions. When making their cases, nominators commonly did not limit themselves to describing and assessing only the merits of contributions—they also assessed contributors. Similarly, in its deliberations, in addition to assessing the impact and significance of contributions (single or multiple), the Turing Committee also considered

[173] New knowledge and inventions in computing are produced by both practitioners and scientists, but they have different criteria of impact and success (usability versus insights). The archival materials did not provide any evidence of creating a comprehensive measure of impact that would respect the differences in achievements of practitioners and scientists.

prior eminence, intellectual prowess, and publication record of a candidate, thus shifting the focus of evaluation to assessing a person, rather than his/her contributions (see chapter 4*: Award-Winning Contributions)*. Furthermore, the archival records produced little evidence of the use of any other measures when assessing award candidates beyond a peer review, testimonies in "at least three" letters of recommendation, and personal knowledge. Considering the available information, three out of four conditions for particularistic allocation of rewards—ambiguous standards of evaluation, computing being a less developed scientific paradigm, and secrecy of evaluation process (see Long & Fox, 1995, pp. 62-64)—appear to describe the decision-making for the Turing Award. Not surprisingly, under the conditions of uncertainty, the actual processes of evaluation and selection for the award involved an overlooked practice of identifying both (1) an important contribution (the work and its merits), and (2) a prize-worthy contributor (the person and his/her merits).[174] The indivisibility of evaluations of contributions from assessment of contributors is a challenge facing the Turing Award Committee and most likely other award committees.

d) Available archival records related to the final selection of candidates revealed that the selection procedures were informal and varied somewhat over time. The final selection (i.e., the "manufacturing of consent") was achieved through mathematical means by averaging preferential rankings. This method may have appealed to committee members' scientific sense of fairness; however, it transferred sentiments into numbers without revealing the reasons or bases of their judgments. This method of voting also was likely to disadvantage candidates less known to committee members (chapter 4*: Award-Winning Contributions*).

Question 2

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[174] Some researchers (Lamont, 2009; Hirschauer, 2010) have argued that particularistic judgments are inherent to an evaluation process that is not "automated" but in which individuals and their preferences must construct merit. Further research can explore the merits of both approaches.

The following findings emerged with regard to the education and career-related factors associated with award winners on their pathways to contribution and recognition:

a) Similar to Nobel laureates, examined by Harriet Zuckerman (1977), Turing Award scientists (n=55) received their training at a few[175] prestigious institutions. In particular, the studied group of American Turing Award winners (n=30) and the control group of scientists (n=30) obtained their Ph.D. degrees at top research universities[176] (i.e., those with very high-level research activities) and some with very distinguished advisors (about 30%). About 27 percent of advisors of future Turing Award winners had also received a Turing Award, and 30 percent of advisors had more than one student who had won a Turing Award, thus indicating a notable amount of continuity in research lineage among awardees (similar to Nobel laureates, see Zuckerman, 1977). In regard to research productivity and the impact of advisors and their students, advisors who were highly productive and highly cited were more likely to train highly productive and/or cited students (among both Turing winners and the control group). Similarly, advisors who had published with their students were, themselves, productive or eminent, as were the great majority of their students. The influence of advisors is critical for training the next generation of successful scientists (Fox, 1983, 1985; Zuckerman, 1977). By providing inspiration, motivation, and the opportunity for skill development, an advisor enables the developmental process that promotes the career success of a protégé (Cotton, Shen, & Livne-Tarandach, 2011).

b) Small differences between the awardees and the control group began to emerge during graduate training. Upon graduation, the eventual Turing Award winners had a greater number of early career advantages than control group scientists: 1) They received graduate fellowships (10% compared to 0% of control group scientists); 2) twice as many

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[175] The 41 winners from the United States attended only 16 institutions, many of which are the same elite universities attended by Nobel Prize winners (Zuckerman, 1977, p. 90) and a few other universities known for their departments of computer science.

[176] Among thirty winners and thirty non-winners used in comparative analyses, fifty percent (in each group) went to five universities that would become the top five computer science programs, see Chapter 5: *Education Attainments of the Awardees.*

of them (30%) published with their advisors; and 3) twice as many of them (47%) found jobs at the top five computer science departments in the United States. In other words, Turing Award scientists were incorporated into research and research-intensive scientific organizations early on in their careers compare to the control group of scientists.

c) Although both the Turing and control group scientists mainly worked in the academic and industrial sectors, they differed with regard to the type of organizations for which they worked (chapter 6: *Career Achievements of the Awardees)*. Almost twice as many of Turing Award scientists (77%) worked in the top five[177] universities in computer science at some point in their careers, compared to the control group scientists (40%). In industry, Turing Award scientists were more likely to work for IBM than control group scientists and thus to benefit from the visibility, the eminence, and the research funding of this computer industry leader. By contrast, the control group scientists were either self-employed or worked in laboratories, government agencies, in lesser known companies and universities, and may have been isolated from the research community (and possibly from research). As a result, they may have had lower visibility and weaker impact in the computing community.

d) The career-related factors that differentiated[178] Turing Award winners from the control group scientists can be summarized as follows: Turing Award winners had more 1) *early advantages*; 2) prior *eminence* (i.e., Turing Award scientists had four times as many awards as the control group); 3) *collaborators* in general and in particular those who were *members of the Turing Committee* (i.e., eight times as many committee members as the control group scientists had Turing Committee collaborators); 4) positions at *top/elite universities* at the time of the award (Turing scientists were three times as likely to be employed at elite universities at the time of the award than the control group); and 5) more *visibility in the ACM* (see chapter 6: *Career Achievements of*

[177] They are Stanford, MIT, University of California at Berkley, Carnegie Mellon University, and Cornell.
[178] Group differences between Turing Award winners and the control group of scientists in education and career dimensions are based on a comparison of group means and a t-test (independent two-sample t-test, equal sample sizes, equal variance) of differences in means presented in chapter 6.

the Awardees). Additionally, Turing Award winners had higher productivity and their publications received twice as many citations as those of control group scientists prior to the year of the award (but these variables were not statistically significant). Also, winners had almost three times as many collaborators who won the Turing Award than did the control group.[179]

e) The career-related factors that were associated with Turing Award winners and were most effective in logistic regression analyses in predicting the likelihood of being a Turing Award winner were 1) being employed in *an elite university*, 2) having received *prior awards*, 3) having started a career with *early advantages*, and 4) having had professional *visibility in the ACM*. The regression results offer an opportunity to conceptualize the way in which recognition with the Turing Award operates: the Turing Award is likely to be bestowed on those scientists who started their careers with early advantages and accumulated other attributes of recognition in the form of awards and positions at prestigious organizations and whose contributions to computing have been noted in the ACM community. When these factors overlap (a winner possesses all the attributes), it is difficult to disentangle the bases for recognition (visibility, location, productivity). However when the winner has only some, but not all of the attributes, the data invites further exploration of justifications used in selection for the award.

In chapter 4, I examined the career factors associated with Turing Award winners and the criteria used by the Turing Award Committee in its deliberations: significance of contributions, prior eminence, intellectual prowess,[180] and publication record. It was reasonable to assume that criteria such as a strong publication record, significance of contributions, and even intellectual prowess would be reflected in publication and citation measures used in the regression analyses. However, the results of logistic regressions

[179] However, these differences in publications, citations, and the number of collaborators with the Turing Award were not statistically significant. Given a small number of observations, lack of significance does not imply that the differences do not exist, instead that the current sample is insufficient for detecting the effect (see Moore & McCabe, 1999, pp. 475-481).

[180] The judgments of intellectual prowess should be investigated in the future research projects for its ability to impact recognition (e.g., Do scientists nominate and select for awards those who they think have superior intellectual abilities?).

revealed that neither citations, one of the measures of the significance of a contribution, nor publication rate differentiated winners from non-winners of the Turing Award.[181] Prior awards, on the other hand, corresponding to the committee's criteria of prior eminence, not only differentiated winners from non-winners but also were the most important characteristic distinguishing the two groups in the QCA analyses. Though visibility in ACM was not part of the criteria used by the committee, it had some bearing on the consideration for the Turing Award. These findings supported the conclusion that, while producing research and contributing to the ACM computing community were nearly prerequisites of being considered for the award, the excellence and significance of prize-winning contributions were not evident in productivity and impact indicators (productivity rate and the highest citation count did not differentiate winners from non-winners of the Turing Award).

A contribution worthy of a major award in computing is likely to be more than an "incremental" work, but rather an achievement that went beyond standard metrics.[182] When the proof of a large increment is neither evident (as in the absence of a high number of publications and citations) nor explained in award citations, the increment appears to stem solely from the judgment and knowledge of the Turing Committee and its selection process.

f) This study also tested which collaborators had the most influence on receiving a Turing Award. Colleagues familiar with the work of a scientist, sharing common research interests or values, and especially those who already won the award or who were Turing Committee members, were particularly well positioned to be "reputational entrepreneurs" – the parties with the "motivation, narrative facility, and institutional placement" to create a reputation (image) for a candidate (Fine, 1996, p. 1162). Among the three collaborative variables—*number of collaborators*, number of *collaborators with the Turing Award*, and collaborators who were part of the *Turing Committee*—only the

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[181] See Appendix G, which pertains to the publication patterns in computer science.
[182] I owe these insights to my advisor, Dr. Mary Frank Fox.

last (committee members) was an effective predictor of winning. Furthermore, the correlation among a set of variables— coauthors with a Turing Award, coauthors who are members of the Turing Committee, and employment in an elite institution— suggested that having "useful" and renowned collaborators was strongly associated with being in an elite institution (i.e., such structural position increases one's visibility and social capital). Collaborators represent "social capital" through which scientists can access resources and rewards (Burt, 1992; Coleman, 1990; Granovetter, 1973, 1985; Lin, 2001). Networks of scientists often form around a particular problem area (Price's "invisible college"), and they are likely to function as "moral economy" (Daston, 1995; Shapin, 1994) in which members feel compelled to nominate colleagues they respect the most.

IMPLICATIONS

These findings have the following broader implications that enhance the understanding of scientific careers, scientific contributions, and recognition in computer science.

1. The findings on award-winning contributions and the selection process (question 1) testify to the challenges facing evaluators of contributions for prizes in computer science (with implications for other interdisciplinary fields) in regard to 1) area of contribution (whether it is central to computer science or not), 2) unit of contribution (a particular problem, an artifact [system, language, algorithm, data structure] or life-long contributions), 3) evaluation criteria (what evaluation measures to apply), and 4) selection method (whether averaging preferential ratings is the best way to reconcile differences among evaluators). These challenges have consequences for the field in the long run. The selection committee, while exercising personal preferences, creates a social hierarchy[183] that impacts all computer scientists. The definition of merit depends on the social criteria of success (Sen, 2000) and since nomination and selection criteria are defined by a small group of people, the outcomes are dependent on *who* defines the criteria and decides on a winner. As a result, clarity of the selection rules has a strong

[183] Bestowing an award is a mechanism for creating a status hierarchy since "every selection of one is a rejection of many" (Young, 1958/1967, p. 15).

bearing upon the perception of fairness and beliefs in legitimacy—the elements that are not only “essential in preserving vitality of research” (Lamont, 2009, p. 249), but that also may impact the participation and the contribution of aspiring groups to the field. Because prizewinners become ambassadors of their disciplines (Cole & Cole, 1973), prizes and awards are an integral part of an evaluation and communication system of science that provide information to the scientific community and to the public at large about excellence and to the identity of the discipline. When the answer to “why” was someone chosen is not apparent, it casts questions, or at least uncertainty, about the functioning of the system, and the extent to which it is operating meritoriously.

2. The factors that are associated with Turing Award winners and strongly differentiate them from the control group of computer scientists— early career advantages, the location in prestigious universities, prior awards, and visibility in ACM—suggest that the award augments the honors already achieved (received prior to the Turing Award). Winners had more prior awards and were associated largely with top research universities while non-winners had fewer awards and were associated with less prestigious universities. While it may not be possible to tell whether research productivity or recognition are the cause or the effect of one’s institutional location, those who get jobs in top research universities have much to gain from the conditions for research, access to eminent colleagues, and visibility within the scientific community. Affiliations with prestigious organizations, collaborations with eminent colleagues, and centrality in the computing community appear to go together with the contributions that went beyond standard “metrics” (publication and citation)—those recognized by the Turing Award.

Some scientists may argue that, above all factors, the choice of research question sets prize-winning scientists apart from non-winners.[184] While the choice of research question may potentially explain early career advantages of Turing Award winners, the

[184] Other factors include prior experiences, association with creative environments and social validation (Merton, 1972, p. 459); transformation of recognition into resources for further work (Zuckerman, 1977, p. 62); scientists’ adjustment to the expectations of institutional settings (Hermanowicz, 2009).

problem choice after the graduation is likely to be influenced also by employing organizations (supporting/impeding research, creating environment for creativity, and risk taking). The study of scientists by Hermanowicz (2009) confirmed that behavior and aspirations of scientists conform to the performance expectations of employing institutions. Consistent with his conclusion, this study found that many non-winners worked in less prestigious and less research-intensive universities (than top five institutions) that may have influenced their problem choice, access to resources, and their chances for recognition (see chapter 5).

3. Scientists can benefit (or not) from the visibility and the prestige of the organizations for which they work. For their first jobs and at the time of the award, Turing Award scientists were more likely than non-winners to work in top research universities. The visibility and the material and human resources of these organizations were likely to facilitate the ways and means for their research and positively affect their chances of recognition. Additionally, peers in top universities or companies may feel more assured in nominating a fellow colleague, who, in turn, would be more favorably perceived by the Turing Committee because of his/her affiliation.[185] On the other hand, the lack of visibility of scientists in less-renowned organizations would result in their being less likely to be nominated and selected for awards.[186] Admittedly, the human ("social/organizational conditions") and material resources of these lower-ranked institutions do not foster high levels of research (Hermanowicz, 1998, 2009) and research performance. However, if an important contribution were to be made in such a setting, it is unclear whether it would have been noticed and nominated for the award. Future

[185] In fact, once a package has been put together, it may be sent to more than one place, potentially leading to more than one award. I observed that awards and election to the National Academies are often close in time and awarded in consecutive years.

[186] Research takes place in less prestigious universities and pockets of performance may exist in less research-intensive institutions (see Hermanowicz, 2009). Would important contributions originating in those settings have equitable chances for recognition? Low visibility and prestige of some institutional affiliations may require conscious effort on the part of peers and organizations to broaden the pool of eligible candidates and increase their chances for nominations. At the same time, the Turing Committee has to take extra measures to ensure that such candidates get fair evaluations and, if selected, their accomplishments receive a fair amount of publicity since the computing community would be less familiar with the candidate.

research can examine what motivates and enables scientists to nominate colleagues for awards. A question that deserves particular attention is *who* nominates and *why*?

4. Mechanisms of recognition are important for the functioning of science, and it is in the interests of scientists that due-recognition is given and that it be based on merit. The ethos of universalism maintains that any judgment of scientific claims not "depend on the personal or social attributes of their protagonist" (Merton, 1942/1973, p. 270). Since the institutional goal of science is to advance knowledge, "recognition and esteem accrue to those who have best fulfilled their roles, to those who have made genuinely original contributions to the common stock of knowledge" (Merton, 1973, p. 293). Recognition of priority of contribution constitutes the property rights in science, and is tied to "recognition by others of the scientist's distinctive part in having brought the results into being" (Merton, 1973, p. 295). By bestowing an award, selection committees acknowledge (and in some cases define) scientists' intellectual property. When recognition is not given, a scientist loses his or her scientific property (Merton, 1973, p. 294). The outcomes may lead to not only "deep moral indignation"[187] but also the abandonment of the science and technology enterprise altogether.[188]

Awards make history by providing visibility to some scientists and withholding it from others, by defining "worthy" research (and to whom) and by rewarding performance. The value of an award is its capacity to recognize "important" achievements in the areas (and dimensions) that the award was established to honor. Although nothing prevents organizations from bestowing an award, with or without any rationale, the value of an award lies in its recognition of what has been achieved. The more visible an award, the more accountable an awarding organization is to the scientific community for the claim of matching the symbolic purpose of the award to the achievement. Not surprisingly, highly visible award-giving organizations in science

[187] Merton (1973) pointed out that the friends and followers are the ones who often "see the assignment of priority as a moral issue" (p. 291).

[188] A recent case of Grigori Perelman and possibly of women scientists and engineers as explained by the leaking pipeline model exemplify this outcome; see Alper (1993) and Gurer & Camp (1998).

(e.g., the Nobel Foundation, the Shaw Prize Foundation, the Inamori Foundation, the Clay Institute, and the ACM) are likely to be held accountable for their claims. Award citations represent justifications and "claims" of worthiness that scientists take seriously, and are likely to hold the claiming organization accountable for the validity of the attributing credit, the underlying justification for the award, and the rigor of the selection.[189] As a result, with the visibility of an award comes the responsibility to establish a fair process for the selection of candidates. Having full control of the evaluative process, a selection committee takes on the difficult job of accepting and reviewing nominations and then strengthening the justifications for the merits of a specific contribution. Their justifications (which are not often apparent) serve as an acknowledgement of the individual contribution of the award winner.

Award-giving organizations seeking to increase the value and credibility of their awards need to consider and address issues surrounding the process of selection and the procedures for nominations. As a set of recommendations, I suggest that awards committees clarify and address a set of challenging questions in their guidelines:

a) What is a unit of contribution and what type of contributions does the award recognize?

b) What dimensions of a contribution shall committee members evaluate?

c) Do any objective measures of impact support the individual testimonies of nominators?

d) Is a nominee's intellectual property (contribution) clearly defined or are there other persons connected to the nominated contribution?

e) What subfield does the contribution represent?

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[189] A recent case involving a Nobel Award provides an illustration. A Nobel Award in Physics was awarded last year (2010) to physicists Andre Geim and Konstantin Novoselov of Manchester University, UK. The explanation for the award posted online and the quality of scientific background issued by the committee upset fellow graphene researchers, including Walt de Heer of Georgia Tech. De Heer wrote a letter to the committee pointing out a series of errors and wanted "to have the record set straight on the document" because Nobel standards "have to be higher than for any other Award and they're not" (Reich, 2010). The background document was said to contain inaccuracies and exaggerations and read as a nomination letter. However, as the Nobel committee is protected by secrecy, it did not reveal what information the committee used. Such criticisms exert a pressure on evaluation committees to account for their decisions and provide accurate information regarding a contribution.

f) Does the committee give deserved attention to non-traditional candidates and/or those lesser-known candidates with less prestigious backgrounds? What is the committee's track record and capabilities in discovering new and/or not well-known stars?

g) What are the committee's policies regarding its members' promoting former collaborators and the eligibility of committee members for future awards?

From a decision-making perspective, the Turing Committee is interested in reducing the risk of awarding a candidate who may not be acknowledged as "worthy" by other computer scientists. In addition, the constraints of time and imperfect information available to the selection committee increase the pressure to select an already eminent scientist. However, a potential outcome of such selection is that it diminishes the likelihood of lesser-known candidates of being recognized. Although the bounded rationality (Simon, 1947) of the committee is likely to result in a satisfactory solution (Simon, 1947), a simply "satisfactory" solution may not be sufficient, considering that the awards have the capacity (and thus the payoff) to generate interest in scientific endeavors[190] and attract attention to scientists and their field (Gingras & Wallace, 2010). Having a previous Turing Award winner on the selection committee may appear to be a good strategy for identifying other quality candidates, however, it may lead to the conferring of awards to collaborators (familiar to the committee member), students, and recognizing only some research areas.

Similar to findings of other peer review studies (Hirschauer, 2010; Lamont, 2009; Musselin, 2005/2009; Travis & Collins, 1991), peer review for the Turing Award has benefits and limitations. The benefits of informal procedures of peer reviews may include a degree of efficiency when dealing with uncertainty—processing available information about nominees and identifying the best candidates within a short time frame and without extensive support. However, previous research has found that peer reviews also have significant limitations: they are subject to power relations, chance, or pre-determined ("in the bag") outcomes (Musselin, 2009); they produce decisions based on

[190] ACM officials see awards as means to promote their discipline. "In my view," commented the president of the ACM, "more awards give us the chance to honor more of our members and more opportunities to tell outsiders stories about what I do, and thereby improve our image in society. Once again, these stories also serve us all by helping attract the best and brightest to IT" (Patterson, 2005, p. 28).

"cognitive particularism"[191] (Travis & Collins, 1991); they have a tendency to select people who are similar to the reviewer (Musselin, 2009; van den Brink, Brouns, & Waslander, 2009), and they are vulnerable to personal tastes and idiosyncratic judgments (Lamont, 2009). Musselin's (2009) study of academic hiring described the judgments involved in evaluation as being "neither random nor characterized by scientific rigor" (p. 202), thus "only imperfectly fit[ing] the norms of scientific meritocracy" (p. 203). Lamont's (2009) study of peer-review revealed that academicians had strong beliefs in the fairness of peer reviews but took for granted the social (interactional) and cognitive nature of decision-making process. Specifically, that the definition of excellence is "rooted and arise[s] from [reviewers'] networks of colleagues and ideas" (Lamont, 2009, p. 241). The findings presented in this study suggest that peer review for the Turing Award, with its informality and ambiguous evaluation criteria, is likely to be subject to the same limitations described in other studies and can benefit from re-evaluation and improvement. The first important step in improving the evaluation process for the Turing Award is to clarify what exactly the Turing Award rewards (address its dual purpose)—the excellence of a contribution or the contributor.

Another important benefit of peer review is that the evaluation is conducted by peers according to common standards and with flexibility to consider multiple factors and nuances. However, just as evaluations for hiring academics are not solely based on the merit of contributions (Musselin, 2009), so may be the case with award evaluations. The decision and the choice of award winners is likely to be the (political) outcome of weighting multiple factors (e.g., age, area of contribution, functionally relevant or irrelevant preferences of the committee), and not simply the merit of contributions (including publication measures or citations). The flexibility that gave peer review its strength, in the absence of consensus and clear criteria for evaluation, opens peer review

[191] "Cognitive particularism" describes decisions based on a particular (similar) scientific school of thought (e.g., discipline).

to a potential application of functionally irrelevant factors in the selection of award winners.[192]

LIMITATIONS OF THE STUDY

The two main questions of this study were constructed to identify broad patterns associated with successful careers leading to recognition with a prestigious professional award. The questions did not address whether recognized contributions were "incremental" or went "beyond any metrics," and whether any biases or discrimination took place. The data/evidence in this study are thus limited in addressing the extent of "equity."

The study examined a small group of distinguished computer scientists with relatively privileged backgrounds and compared them to scientists from similarly privileged background. The comparison with scientists from other institutions (e.g., less research oriented) or organizations is likely to uncover more differences. Thus, it is not known how well the findings of this study will apply and, using the same variables, could estimate the chances of receiving a Turing Award for scientists from other institutions. The use of standard scientific measures of productivity (peer reviewed publications and citations) could be enhanced in future investigations of winners of awards by including other metrics of productivity, contribution and impact such as all published works, patents, product usability data, for example. However, one important aspect remains—the recognition with a Turing Award is likely to go "beyond standard measures" by awarding contributions (and contributors) that have special properties.

CONTRIBUTIONS

This study of Turing Award winners contributes to the existing body of knowledge in the sociology of science by illuminating the characteristics of excellence of prize-winning contributions and of education and careers of award winners compared to non-winners. The design of this study extends the design of prior research of scientific

[192] Long and Fox (1995) provided evidence for such outcomes.

elites (Zuckerman, 1977) that examined only those apprentices who "in fact entered the aristocracy of science," thus leaving a gap of knowledge about the careers and contributions of "the other apprentices of the same masters who, for one reason or another, did not later move into the upper strata of the scientific community" (Zuckerman, 1977, p. 123). The findings increase the understanding of stratification in scientific recognition (awards being the mechanism of stratification) in a comparatively new and interdisciplinary (in origin) field of computer science. While award-winning contributions were broad and diverse, covering the domains of science and technology/engineering, the outstanding qualities of contributions (or of the contributors) were not conveyed by citations and publication rates. The productivity and impact measures did not differentiate Turing Award winners from non-winners, leaving a large share of the recognition of merit to the discretion of the Turing Committee members. Instead, career factors conveying eminence, visibility, and prestigious affiliations of contributors were more strongly associated with being a Turing Award winner.[193] These findings suggest that the actual excellence of contributions has not been fully captured, explained, or communicated by the Turing Award to the computing community and to the public at large.

The findings raise a need to consider the selection process and find better ways to communicate the excellence and outstanding qualities of award-winning contributions. Clear evaluation and selection methods could help to define excellence, which, in turn, may encourage new contributions. As a result, the findings call attention to the importance of improving the design of nomination, evaluation, and selection procedures

[193] The study also contributes to the ongoing debate about the means of predicting award winners. For many years, the ISI tried to predict Nobel Prize winners in medicine, physics, chemistry, and economics from citation counts (Brynco, 2010), but with a low success rate of only 3.41 percent (3 winnings out of 88 naming events) for a four-year period from 2002 to 2005 in (Liu, 2005, p. 296). The present study revealed that other factors, such as prior awards and institutional/organizational affiliations, are likely to be better predictors (regardless of whether they should be or not). Additionally, the profile of Turing Award scientists developed by this study can serve as a valuable instrument for assessing how other scientists measure up to the Turing profile. Subsequent research could investigate two subgroups: women pioneers in computer science and co-authors of Turing Award scientists who appeared in highly-cited publications but who did not receive the award.

for the Turing and other awards in computer science. Redesigning these procedures requires close attention to the critical roles that peers and organizations play in facilitating or impeding the process of recognition. If neglected, these processes are likely to reproduce existing (personal, institutional, disciplinary/cognitive, gender, race/ethnicity) power relations, but if addressed, they can promote excellence in research, thus opening careers to talent and encouraging contributions to the field of computer science.

APPENDIX A

NOTE ON ORIGIN OF THE TURING AWARD AND COMPARISON WITH THE NOBEL PRIZE

1. Origin of the Turing Award

The Turing Award has surprisingly humble origins as an honorary annual lectureship award. Alan J. Perlis, past president of the ACM, was the "the first designee for ACM's new honorary award" ("Perlis Invited as A. M. Turing Lecturer for 1966: First Time ACM Honor is Bestowed," 1966, p. 47). Originally called the A. M. Turing Lecture Award, it was created "as one means of giving adequate recognition to outstanding persons currently in the computing and information sciences area" ("Perlis Invited as A. M. Turing Lecturer for 1966," 1966, p. 47). Until 1978, the award was accompanied by a $1,000 honorarium that was subsequently doubled. A five-member Turing Award Committee, one of the ACM Awards subcommittees, is responsible for the selection of the Turing Award winner.[194]

The Turing Award advances the organizational purpose of the ACM. As noted by Stuart Feldman, President of the ACM in 2007, the visibility of the award is beneficial because the size of the award "attracts interest from outside the field and validates its importance" (Feldman, 2007, p. 18). While most awards given by professional organizations remain relatively low key,[195] several prizes have sizable, "flashy" cash funds. For example, in 2010, the Kyoto Prize for "scientific, cultural, and spiritual

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[194] The Turing Awards Committee consists of five voting members. One member is appointed each year by the president of the ACM upon the recommendation of the chair of the Awards Committee for a five-year period (in consultation with ACM Policy and Procedures Guidelines). The procedures that the ACM award committees follow state that each committee works "according to its own historical pattern and rules set out by the chair" (Ryan, 1989, September 19).

[195] Unlike the IEEE-CS that awards small (and thus egalitarian and honorary) awards, the ACM opted for one large award. A significant difference in award amounts alludes to the importance of individual contributions in computing as opposed to collaborative work practices in engineering, the difference in cultures of computing and engineering, and perhaps a greater need in computing to draw attention to its field.

betterment of mankind,"[196] presented in the categories of advanced technology, basic sciences, and arts and philosophy, was about $550,000, the Balzan Prize in sciences and humanities was $1 million,[197] and, of course, the most prestigious award, the Nobel Prize was about $1.5 million. As the cash prize for the Nobel Prize mounts, it exerts pressure on other organizations such as the ACM to increase the monetary values of their prizes and thus their ability to match that of the Nobel Prize.

In its short existence, the honorarium for the Turing Award has increased with the aim to maintain its visibility and prominence in response to competition and the proliferation of awards. In a letter dated August 7, 1987, to the chair of the Awards Committee, Juris Hartmanis (who later received a Turing Award in 1993), pointed out that the $2,000 honorarium was "not inadequate," but "embarrassing," and urged the committee to raise the Turing Award substantially or "the prestige of the Turing Award [would be] in great danger as other prizes are created and/or their awards are increased" (1987, August 7). In particular, Hartmanis cited the "massively financed" Kyoto Prize awarded to Claude Shannon in 1985. Computer science, wrote Hartmanis, requires "the prestige and the attention which comes with a well-recognized prize rewarding and drawing attention to the best work in our field" (1987, August 7). The suggestion to increase the Turing award to "as large as politically and practically possible" was a means of maintaining the prestige of the award and its claim of being the "Nobel of Computer Science." He wrote, "…we must increase the Award and insure that the laureates justify and enhance its prestige." The award was subsequently increased to $25,000 in 1988, to $100,000 in 2002, and to $250,000 in 2008, in part, to keep up with other notable awards.

2. Comparison with the Nobel Prize

In its claim of being the "Nobel of computing" (Lynch & Herzog, 1995), the Turing Award warrants a comparison with the most prestigious scientific honor, the

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[196] Retrieved April 26, 2011 from http://www.inamori-f.or.jp/e_kp_out_out.html

Nobel Prize. Unlike the Nobel Foundation, which was created with a substantial budget and elaborate procedures for selecting and bestowing prizes, the ACM, as a scientific society, has worked with limited human and financial resources and developed informal and (procedurally) efficient selection procedures.[198] Structuring the selection process at the Nobel institution was not easy as it had its share of difficulties (see Crawford, 1984) at the start in enlisting the cooperation of key players (the Royal Swedish Academy of Sciences, the Swedish Academy [of literature], the Karolinska Institute, and the Norwegian Storting [parliament]). The common rules and procedures ensured the participation of these four institutions in awarding five (and now six) prizes in physics, chemistry, medicine/physiology, literature, and peace (and later, economic sciences).

Unlike the Nobel Foundation, the ACM bestows a Turing Award in only one field, computer science. However, both organizations are international and aspire to recognize contributions from around the world, at least in spirit.[199] In both cases, the actual evaluations and decisions are primarily made by peer scientists (the ACM Turing Committee is partly composed of industry professionals without a Ph.D.). One of the main differences between the organizations is that the Nobel Prize has very stringent stipulations on who holds nominating rights. For example, in physics, the right to submit the nominating proposals is enjoyed by

1. Swedish and foreign members of the Royal Swedish Academy of Sciences;
2. Members of the Nobel Committee for Physics;
3. Nobel laureates in physics;
4. Permanent and assistant professors in the sciences of physics at the universities and institutes of technology of Sweden, Denmark, Finland, Iceland and Norway, and the Karolinska Institute, Stockholm;

[198] Internally, ACM is proud to have a “grassroots” feel.
[199] Alfred Nobel’s will stated, “It is my express wish that in awarding the prizes no consideration whatever shall be given to the nationality of the candidates, but that the most worthy shall receive the prize, whether he be a Scandinavian or not.” Retrieved April 26, 2011, from http://nobelprize.org/alfred_nobel/will/will-full.html. In the case of the Turing Award, I noted mainly the “trans-Atlantic” affiliation of award winners.

5. Holders of corresponding chairs in at least six universities or university colleges selected by the Academy of Sciences with a view to ensuring appropriate distribution over the different countries and their seats of learning; and

6. Other scientists from whom the Academy may see fit to invite proposals. [200]

Thus, no one can nominate someone for a Nobel Prize unless they receive an invitation to do so, which limits the chances of some scientists (without ties to Swedish scientists or Nobel Prize winners) to be nominated. After nominations have been received, the first selection is made by the Nobel Committee for Physics (traditionally consisting of five members), which compiles a report with nominations for the Royal Swedish Academy of Sciences, which then selects the Nobel laureates through majority rule.[201] In case of the ACM (since 1976), since it does not explicitly restrict who can submit nominations, members of the society and non-members can nominate candidates for the Turing Award. The Turing Award Committee of five (voting) members decides on a winner. As such, a smaller number of people decide on the Turing Award, compared to the Nobel Prize. While the final selection must testify to the fact that the contribution lives up to the criteria and purpose of the award, nothing can guarantee that a selection was made through a deliberate (if not scientific) process, free of bias and discrimination, in the case of either the Nobel or Turing prizes. The level of transparency of the process, after all, is limited by statues or practices preserving secrecy.

The Nobel Prize exerts pressure on new and existing awards to keep up with the cash prize and the visibility of the Nobel Prize. As mentioned above, the Turing Award had to increase its cash fund a number of times. While the cash fund for the Turing Award ($250,000 in 2010) is set far below the Nobel Prize (about $1.5 million in 2010), the growing number of technical awards[202] and their monetary fund escalate the pressure to raise the cash fund for the Turing Award. While not many new fields can attract

[200] "Nomination and Selection of Physics Laureates." (n.d.). Retrieved from http://www.nobelprize.org/nobel_prizes/physics/nomination/

[201] The official information about nomination and selection processes is available on the website of the Nobel Foundation: http://www.nobelprize.org/nobel_prizes/physics/nomination/

[202] Just recently a new award was announced—Queen Elizabeth Prize for Engineering—the Nobel equivalent for Engineering which comes with £1 million.

sponsors willing to contribute a million each year for a cash fund, each field perceives itself as being entitled to having its "own Nobel Prize." The proliferation of awards creates and greatly increases the "machinery" for selecting a winner. It is here—in the evaluation and selection criteria and procedures—where changes and innovations are needed, but the prizes are, unfortunately, not rated nor do they compete in these measures.

APPENDIX B

NOTE ON INDUSTRY SCIENTISTS, TURING AWARD WINNERS WITH A PH.D., N=3

Three industry scientists, John Cocke, Jim Gray, and Alan Kay, have won the Turing Award in 1987, 1998, and 2003, respectively. John Cocke graduated with Ph.D. degrees from Duke University. Jim Gray attended the University of California at Berkeley. Alan Kay earned his Ph.D. at the University of Utah. Only one of these universities is among the top five programs in computer science. Cocke majored in mathematics while Gray and Kay majored in computer science. Only one of them received an early career advantage (first job), none had a fellowship (although Gray was sponsored by an NSF grant), nor did they publish with their advisors. Upon graduation, Gray and Cocke joined IBM while Kay started working as a researcher at Stanford University. The careers of these industry scientists were marked by low (by academic standards) publication productivity (only Gray exceeded the Turing group average of 28 by having 32 publications prior to the Turing Award), and fewer citations than other Turing Award scientists (their most cited publications had 37- 46 citations while the Turing group average was 199). Their collaboration networks, however, were larger (for both of them) than the Turing group average of 25.7 coauthors. Cocke and Kay were fortunate to have two to three Turing Award scientists among their co-authors.

All three scientists became relatively eminent through prior awards. Whereas Kay had only one award, Cocke and Gray had three and six, respectively, some of which were from the ACM. For the entire duration of his career, Cocke stayed with IBM while Gray and Kay worked for many other well-known in computing companies such as DEC, Microsoft, Xerox, Atari, Apple, and Walt Disney Imagineering.

A number of observations can be made about the careers of industry scientists. First of all, their career profiles are similar to other Turing Award scientists in having prior awards and collaborators with the Turing Award. Even though they were not affiliated with any of the major universities, these scientists benefited from the visibility of computing companies for which they worked (IBM, DEC, Microsoft, Xerox, Atari, Apple, Walt Disney Imagineering – these companies are known for investing in research and development). Industry scientists differed from the studied group of Turing Award winners in their lower than average publication rates (1.22) and lower than average citations to the most cited publications (42 versus 199 for Turing group). However, the scientific measures of productivity and impact may not capture their contributions (and their prominence) in the field of commuting. Low publication rates can be partially explained by organizational norms in which a team, not an individual, gets credit for the success of a project and patents, reports, designs, and other work is often owned and defined by the company.

The careers of scientists and engineers unfold in institutional structures that impact research activities. The work environments of industry and academia differ with regard to their research goals/missions (Kornhauser, 1962; Lacetera, 2009), rewards (Dasgupta & David, 1994; Sauermann & Stephan, 2010), decision-making, openness and information-sharing practices (Cohen, Florida, Randazzese, & Walsh, 1998). While science activities in academia have traditionally focused on basic research and scientific knowledge, science activities in industry have traditionally focused on applied research, utility, and profits. In addition, industry has traditionally been able to offer more monetary rewards while academia has offered more symbolic rewards (even in industry there is a tradeoff between wages and scientific orientation of firms, see Stern, 2004). Most importantly, the organization, not the employed scientists, has often claimed ownership of intellectual property. Scientists in industrial settings also often face restrictions in technical communications, for the industrial organizations have an interest in limiting technical communications to protect themselves against competitors. However, for scientists in academia, communication through publications and information sharing has been an integral part of the profession and an important facilitator of further advances (Cohen, Florida, Randazzese, & Walsh, 1998).

APPENDIX C

NOTE ON WOMEN TURING AWARD WINNERS, N=2

In 2006, Frances Allen was the first woman computer scientist to receive a Turing Award, after 39 years of the existence of the award. Two years later, in 2008, the Turing Award was bestowed on Barbara Liskov. Both women were about 70 years old at the time of the award (Allen was 74, and Liskov was 69). In addition, the Turing Award came after more than 40 years of professional work (an average of 44.5 years from their terminal degrees to their Turing Awards compared to that of 27.6 years for the studied group of American Turing Award scientists). Frances Allen graduated with a master's degree in mathematics (as her terminal degree) in 1957 from the University of Michigan, and worked for IBM all of her career. Barbara Liskov had earned a Ph.D. in 1968 at Stanford University in mathematics/computer science. After graduation, she continued working for the Mitre Corporation, where she had worked after receiving her bachelor's degree, but later joined MIT, where she works to this day.

Graduating with a master's degree, Allen had little chance for obtaining early career advantages such as fellowships, publications with her advisor, or a prestigious job at a top computer science department. Nevertheless, after a short teaching opportunity, she was hired by the most prominent at that time computer company, the IBM, to teach the FORTRAN language. Liskov pursued a different path—an academic career, however, she also did not start with early career advantages. During her doctoral studies she was a Graduate Research Assistant working in the area of artificial intelligence in a lab that was supported by military funding of the Advanced Research Projects Agency (ARPA). She did not publish with her advisor and her first job was not academic. She was hired as a technical staff member by the Mitre Corporation.

The careers of two women Turing Award winners differed in one important way: one of them was an academic (Liskov) while the other was an industry researcher (Allen). Both women had very successful careers but with different indicators of success. Allen's productivity and impact measures (the average of 13 publications, 96 citations prior to award year; a publication rate of 0.27) were lower than that of men Turing Award winners (the average of 28 publications and 199 citations), but not unusual for industry scientists. In regards to collaborative indicators, compared to men Turing Award winners, she had a large number of collaborators (82 co-authors versus 25.7, the Turing group average), and her network of co-authors included one Turing Award winner who already received the Turing Award, and another (Liskov) who would go on to receive the Turing Award in 2008. Allen had other characteristics that I found to be associated with and distinguishing other Turing Award winners: she had two prior awards, a prestigious affiliation (even if not academic), and a collaborator who had been a member of the Turing Committee.

Liskov's academic career unfolded in a university (MIT) with very high research activity and strong emphasis on publication productivity. As an academic, Liskov had more publications than Allen (34 above the Turing group average of 28) and more citations to her most cited publication prior to the Turing Award (231—above the Turing group average of 199). She also had two prior awards but fewer collaborators (46, while Allen had 82). However, two of her collaborators were members of the Turing Award Committee and one was a Turing Award winner, Frances Allen herself.

The profile of Barbara Liskov most strongly resembles the profile of men Turing Award winners: she attended a top university for computer science; she had a high number of publications and citations (more than those of male Turing Award winners); she had prior awards and was a member of the National Academy of Engineering; among her collaborators was a member of the Turing Award Committee, and she published in ACM journals. Frances Allen, on the other hand, differs from the average profile of men Turing Award scientists by having fewer publications and citations but more collaborators. However, she had prior honors, a collaborator who already won the Turing Award, and two who were members of the Turing Committee. (Thus, the study's finding still holds—the Turing Award augmented honors already received).

Three observations can be made about the careers of both of these women scientists. The first is that they both went to Research I universities (with very high research activities) and majored in the "hard" sciences—mathematics and computer science, which opened career opportunities that were typically not available to women without such academic credentials. Second, both of their careers at some point involved teaching, which was typical of women during the mid-20th century. Finally, their candidacies benefited from the high profile and visibility of the organizations, IBM and MIT, for which they worked. However, why it took so long to recognize their achievements remains unknown and a potential topic for post-dissertation research.

Knowing how two distinguished women Turing Award winners differ from other women computer scientists is important for understanding the achievements of women Turing Award winners. Toward that, I undertook a preliminary study of a group of the first women to earn a Ph.D. in computer science in the United States between 1970 and 1976.[203] Table 8.1 provides a summary of the career measures of a sample of women computer scientists, the two women Turing Award winners, and men Turing Award winners and control group scientists.

The first women computer scientists were likely to graduate with a Ph.D. from a diverse pool of institutions, not just the top five universities (30% of the sample of women scientists went to the top five schools compared to 50% of Turing Award and control group scientists, not shown). Women published less and received fewer citations than Turing Award winners but more than the control group of scientists. They had fewer honors and awards compared to Turing Award male scientists but slightly more than the control group. Very few worked in elite universities 27 years after the graduation with a Ph.D. Women scientists had more collaborators than men Turing Award winners and twice as many as the control group of male scientists. However, they had fewer collaborators who won the Turing Award or who were members of the Turing Committee. They had lower visibility in the ACM than men Turing Award winners, suggesting that they belonged to other communities, rather than the ACM.

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[203] I was fortunate to spend a month as a graduate fellow at the Centre for Gender Excellence in Örebro University, Sweden and to begin a study of women computer scientists in the United States which I hope to pursue as a post-dissertation research.

Similar to other women in computer science, the two women Turing Award winners did not start with early career advantages such as fellowships, publications with advisors, or first jobs in the top five departments of computer science. However, the two women Turing Award winners stood out from the average profile of women computer scientists in: 1) prior honors, 2) employment with prestigious companies, 3) and resourceful collaborators—they had more collaborators and among their collaborators there was at least one Turing Award. Thus, the factors that differentiate male Turing Award winners from non-winners also largely apply to women Turing Award winners, with the exception of early career advantages.

Table C.1. Descriptive Statistics: Career Measures for Women and Men Computer Scientists

Career Measures	Women Computer Scientists: Graduates with a Ph.D., 1970-1976 (n=30)			Women Computer Scientists: Turing Award Winners (n=2)		Men Computer Scientists: Turing Award Winners with a Ph.D., 1942-1981 (n=30)			Men Computer Scientists: Control Group with a Ph.D., 1939-1983 (n=30)		
	Mean	Median	Sum	Mean/Median	Sum	Mean	Median	Sum	Mean	Median	Sum
Early Career Advantages											
Fellowships	.03	0	1*	0	0	.10	0	3	0	0	0
Publications with advisor (y/n)	.13	0	4*	0	0	.30	0	9	.13	0	4
First job in top 5 (elite) depts.	.10	0	3*	0	0	.47	0	14	.20	0	6
Productivity											
Publication rate	0.94	.927	28.32	0.73	1.45	1.22	.9	36.6	.84	.45	25.3
Publications total	25.67	14	770	30.5	61	28.23	22	847	21.5	12	645
Impact											
Citations (max)	110	48	3192	163.5	327	198.5	80	5955	90.87	25.5	2726
Eminence (Awards)											
Honors and fellowships	.47	0	14	2	4	1.70	1.50	51	.40	0	12
NAS and NAE memberships	.10	0	3	1	2	.53	.50	16	.03	0	1
Location in an Elite Institution											
Employment in top 5 (elite) depts at the time of the Turing Award	.07	0	2	1	1	.50	.50	15	.13	0	4
Number of Collaborators											
Co-authors	34.41	29	998	64	128	25.7	23.5	770	14.9	7	446
Types of Collaborators											
Co-authors Already Turing Award winners	.13	0	4	1	2	.80	0	24	.30	0	9
Co-authors members of the Turing Committee	.20	0	6	2	4	.50	0	15	.07	0	2
Visibility in ACM											
ACM publications	.53	1	16	1	2	.97	1	29	.57	1	17
ACM awards	.03	0	1	0	0	.33	0	10	.13	0	4
ACM services	.07	0	2	0	0	.03	0	1	.10	0	3

* Data was missing for 6 cases; most likely they were zero

APPENDIX D

COLLECTED DATA AND VARIABLES

Table D.1. Collected Data: Variables and Their Definitions

	Variable Name	Operational Definition
Individual Characteristics	1. **BornYr**	Year of birth of studied scientist
	2. **BornCity**	City (and when known a state) where the person was born
	3. **BornCountry**	Country where the person was born
	4. **MarriedYr**	Year of marriage, if listed
	5. **MarriedAge**	Age at the time of marriage
	6. **Children**	Number of children, if listed at the time of the vita collection and printing of the Biographical Directory
Education	7. **Dgr N**	Number of post-secondary degrees
	8. **BA Yr**	The year of graduation with the bachelor's degree
	9. **BA Inst**	Bachelor's degree institution
	10. **MA Yr**	The year of graduation with the master's degree
	11. **MA Inst**	Master's degree institution
	12. **PHD Yr**	The year of graduation with a Ph.D.
	13. **PHD Inst**	Ph.D. degree institution
	14. **PHDarea**	Area/department of Ph.D. (e. g., math, applied math, industrial administration, physics, political science, EE, communication science).
	15. **Advisor**	Name of advisor
	16. **Adv Pubs**	Number of publications with the advisor prior to the award year
	17. **Adv Students**	Total number of students trained by the advisor from the Clay Institute Genealogy project website.
	18. **Turing Students**	Total number of students trained by Turing Award scientist from the Clay Institute Genealogy project website.
	19. **GradFellowship**	Was Turing Award winner supported by a fellowship (greater than one year) in graduate school? If yes, list the fellowship.
	20. **Interruptions**	Note if any interruptions (gaps between degrees) in education due to WWII, military service, work—the gap in the number of years between the bachelor's and the master's/Ph.D. is longer than the norm of about 6-8 years.
	21. **Aturing**	Is the advisor a Turing Award recipient?
	22. **ASTuring**	Are any of the advisor's students Turing Award winners?
Wor k	23. **Positions**	Total number of positions held prior to the prize year
		Each of the Following Corresponds to Each Position
	24. **Org**	Name of the institution/organization

	25. Sector	Sector of Employment (1 = Academic (department or institute or center or lab within a university) 2 = Industry 3 = Government (agency or lab not centrally a part of university) 4 = Military (ARPA, DARPA, AirForce) 5 = Non-Profit (research center or lab or institute or think-tank or corporation) 6 = Self-employment 7 = Other)
	26. Work Unit	Unit of employment (1=Department 2=Laboratory 3=Institute/foundation 4=Center 5=Agency 6=Corporation 7=IBM 8= Organization (other) 9=Missing)
	27. JobTitle	Title of the job
	28. Position	If Academic, Position occupied (1 = Instructor 2 = Assistant Professor 3 = Associate Professor 4 = Full Professor 5 = Titled Professor 6 = Visiting Professor 7 = Chair of Department 8 = Dean 9 = President/CEO/director/co-director 10 = VP, chief scientists, vice chairman 11 = Fellowships, Institute for Advanced Studies 12 = Consultant)
	29. YrStart	The year the job began
	30. YrFinish	The year the job ended
	31. Yr Empl	Years at the job (YrStart – YrFinish)
	32. Consulting	Number of consulting opportunities during this job (if it was done concurrently with another job)
	33. Advising	Number of advisory responsibilities (boards, etc.) during this job (if it was done concurrently with another job)
Affiliations	**34. ACM member ACM Fyr**	Was the person a member/fellow of ACM? If a fellow, list fellowship year.
	35. IEEE member **36. IEEE Fyr**	Was the person a member/fellowship of IEEE? If a fellow, fellowship year.
	37. NAS **38. NAS Fyr**	Was the person a member of NAS? If yes, the year inducted.
	39. NAE **40. NAE Fyr**	Was the person a member of NAE? If a fellow, the year inducted.
	41. AAAS member **42. AAAS Fyr**	Was the person a member of AAAS? If a fellow, fellowship year.

	43. AMS/MAA **44. MS/MA Fyr**	Was the person a member of AMS/MAA? If a fellow, fellowship year.
	45. Other societies	Was the person a member of other societies? How many? (I use this information to study professional identity of computer scientists.)
	46. List other societies	List those societies in separate columns. (To study professional identity).
	47. Total org member	Total number of professional organizations that a person was a member of.
Honors	**48. HonorsPreA**	How many honors/awards did the person receive prior to the Turing Award?
	49. Honor Title	Title of the honor/award
	50. Honor Org	Honor/award granting organization (ACM = 1, IEEE = 2, US GOV = 3, AAAS = 4)
	51. Honor Yr	Year of the award
	52. TitleProf **53. TitleProf Yr**	Did a person hold a named distinguished professorship? If yes, list year.
	54. PrizeYear	The year when the Turing Award was awarded.
	55. Winner	Turing Award winner or no-winner (Winner=1, non-Winner=0).
	56. AgeAtPrize	Age when the winner received the Turing Award (Year of prize - year of the birth.)
	57. TimeTillPrize	Professional age (time since the last degree to the reception of the Turing Award) (Prize year-year of last degree (BA, BS, MA, MS, or Ph.D.))
		All Publications are Counted Prior (and including) to the Award Year
Publications	**58. Patents**	Does a person have any patents (If known. Very little patent information was available. I could not collect the data on patents.)
	59. PubsTotal	Count of publications from the Web of Science (mostly articles) prior (and including) to the award year in computer and engineering related subject areas.
	60. SoloPubsTotal	Count of the number of solo publications (articles) prior to the award year.
	61. Number of co-authors	Count of the number of co-authors prior to the award year.
	62. Articles	How many of publications were articles?
	63. Books	Number of books retrieved from the WorldCat OCLC database prior to the award year.
	64. ACM pubs	How many of the publications were published in ACM journals/magazines?
	65. Yr First Pub	Year of first publication
	66. Publication with Advisor	Did scientist publish with the advisor (prior to Ph.D. year or 2 years after the Ph.D. year)? (Yes=1; No=0)
	67. Highest citation count	The highest citation count of the most frequently cited publication prior to the Turing Award.
	68. Highest citation publication year	The year in which the most frequently cited publication was published.

APPENDIX E

NOTES ON THE RANKING OF INSTITUTIONS

The first assessments of computer science departments were based on reputational ratings. As early as in 1978, Richard Conway, computer science professor from Cornell university, surveyed graduate programs in computer science by inviting chairs of 71 programs offering a Ph.D. in computer science to rate (not rank) other programs with respect to “quality of graduate faculty” and “effectiveness of doctoral program.” Another assessment was performed by the National Research Council (NRC) that surveyed higher education institutions and supplemented the survey results with data from federal agencies, the Institute of Scientific Information, and the Doctorate Records File. The NRC publication provided information on department size, research support, publications, citations, number of graduate students, and number of minorities. The NRC assessment was published in 1982, 1995, and in 2010. However, the 2010 publication openly admitted that there was “no single universal criterion or set of criteria” for ranking and urged users to assess the reason they needed ranking and choose important measures for themselves (Ostriker, Kuh & Voytuk, 2010, pp. x-2). The latest NRC ranking in addition to research activity also considered such factors as student support and outcomes, and the diversity of the educational environment. Nevertheless, it openly admitted that the most important measures for the quality of doctoral programs were those “related primarily to faculty research productivity” such as publications, citations, grants, and awards that, according to faculty, “matter more than other metrics” (Ostriker, Kuh & Voytuk, 2010, p. 13). I decided to use the older 1995 NRC (Goldberger, Maher, & Flattau, 1995) rankings because they were based on a combination of factors believed to be important in determining effectiveness of doctoral programs: scholarly ratings of the faculty, and program effectiveness in educating research scholars and scientists. These rankings were also primarily reputational, reflecting perception of raters (peers) about the quality of existing programs. However, the same perceptions were likely to be known to and guide computer scientists in their considerations of graduate schools and work places. The 1995 NRC publication identified the top five schools in computer science—Stanford, MIT, University of California-Berkeley, CMU, and Cornell University—that were also the top schools in 1978 Conway's ranking.

The need to rank academic institutions stems from the necessity to understand the paths of Turing and non-Turing Award scientists through institutional structures, in particular, where they received their bachelor's, master's, and Ph.D. degrees (affecting their later careers) and the institutions in which they worked (possibly affecting their chances for contribution and recognition). The task of ranking doctoral programs was complicated by a fact that many Turing Award winners received their terminal degrees in programs other than computer science (mathematics, engineering, physics, industrial administration, even political science). To rank all universities and departments where scientists worked was also challenging because some had worked in departments other than computer science (e.g., Management and Business Administration).

An alternative approach to capturing differences among institutions/programs where scientists worked and studied was to use Hermanowicz's method and divide the schools into three tiers—top, middle, and bottom—corresponding to elite, pluralist, and communitarian worlds, respectively (Hermanowicz, 2009). However, Hermanowicz's classification had a drawback—it did not take into account variations within each academic world that were more pertinent since studied scientists attended only a handful of selected institutions. As a result of this and with Dr. Walsh's suggestion, I restricted the need to rank institutions to only assessing the location of Turing Award and control group scientists in "elite" (top five) institutions during two critical career points: at the time of their first jobs and at the time/year when they received the Turing Award (or equivalent number of years for the control group). The NRC ranking was consistent over time. Among three different surveys from 1978, 1982, and 1995, the top five graduate programs remained exactly the same: Stanford, Massachusetts Institute of Technology (MIT), University of California-Berkeley, Carnegie Mellon University (CMU), and Cornell University. Given that departmental rankings of different disciplines vary within a given institution, the chosen ranking of institutions is based on the survey assessment of academic departments (not institutions as whole) and represents a stable hierarchy of institutions for computer science over time. Given the stability of prestige rankings across 17 years (1978-1995), the time points of institutional assessment of 1978 and 1995, though imperfectly, nevertheless signify prestige status of universities for the studied time period, specifically when scientists got their first jobs (1939-1984) and when they were awarded the Turing Award (1939-2008).

APPENDIX F

TURING AWARD COMMITTEE AND THE DIVISION OF INTELLECTUAL PROPERTY

Award citations are both carefully and less carefully crafted to describe the life-long contributions of people rather than any one specific contribution. The case of Allen Newell and Herbert Simon, 1975 Turing Award winners, provides an example of selecting first the contributors and then crafting the citation so that it reflects their contributions; and, by so doing, assuming another important role—of division and attribution of intellectual property.

Newell and Simon were the first to receive a joint award, but the decision to bestow a joint award was not arrived at easily because committee members were reluctant to give the Turing Award to more than one person (compared with the Nobel Prize, which usually does not award more than three scientists). In this case, the committee members took a poll to determine whether a single person could stand alone or if a joint award was merited. Since Newell and Simon were a mentor and a mentee who had collaborated and published together for many years, the decision was made to award both. However, what makes this case interesting is that if the award citation had been more specific, it would likely have mentioned the originally nominated project (Information Processing Language [IPL]), and a third individual, Cliff Shaw, their collaborator and co-author on two of their most cited publications[204] prior to the award year (1975). Trained as a mathematician (with a bachelor's degree), Shaw was recognized for his careful and precise work in programming at the RAND Corporation. He collaborated with Newell and Simon long enough that their collaboration became known as the "Newell-Shaw-Simon [NSS] consortium, innovators of the Information Processing Languages (IPL I through IPL V)," which are recognized as artificial intelligence languages (Lee, 1995). Besides IPL, Shaw had generated most, if not all, of

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[204] Newell, A., Shaw, J. C., Simon, H. A. (1958). Elements of a Theory of Human Problem-Solving. *Psychological Review, 65*(3), 151-166. Also see Newell A., Shaw J.C., Simon H.A. (1958). Chess-Playing Programs and the Problem of Complexity. *IBM Journal of Research and Development, 2*(4), 320-335.

the programming for three artificial intelligence programs: "Logic Theory Machine," "General Problem Solver," and the "Chess Program." Shaw's work in creating IPL and JOSS (JOHNNIAC Open Shop System) languages is considered a major contribution to artificial intelligence. However, the award committee did not recognize Shaw either as a co-inventor or as one meriting the award.[205]

Omitting Shaw as an awardee, the Turing Award Committee was faced with the task of writing the award citation so that it appropriately recognized the role Shaw played. Thus, the committee requested additional input from Newell and Simon, who asked the committee to add Shaw's name to the award citation "to make [their] debt to Cliff Shaw explicit," since "research teams thrive only when credit is given where credit is due" (Newell & Simon, 1975, Aug. 14). Although credit was given to Shaw, to justify not awarding Shaw as a co-recipient, the committee wrote the award citation so that it fits the range of the contributions of Newell and Simon, not any one contribution in particular. Thus, in the actual award citation,[206] Shaw became one of many collaborators while Newell and Simon were acknowledged for doing basic science.

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[205] Shaw's contributions to innovative research in collaboration with Newell and Simon, were substantial as acknowledged by Newell: "Cliff himself was the genuine computer scientist of the three—I mean in some fundamental way in which I'm not a computer scientist, okay? Cliff was the guy who had developed an assembler, really knew and operated with the machines and so forth. I was very much a middleman—not in the social sense, though that was also true by the way—in the sense that I didn't operate with the machines directly [located miles away from each other they communicated by letters and telephone], and I never had. By programmer, you shouldn't think that I was dictating to Cliff what to do. He was the one guy who understood what computers are all about. I've always had sort of a large capacity for a mass of detail in terms of specifying large systems, and Herb has much less tolerance for that. Cliff himself also has a very large tolerance for detail, but he also had all the programming skills and understanding of machines which I didn't have" (McCorduck, 2004, pp. 169-170).

[206] The citation stated, "In joint scientific efforts extending over twenty years, initially in collaboration with J. C. Shaw at the RAND Corporation, and subsequentially with numerous faculty and student colleagues at Carnegie-Mellon University, they have made basic contributions to artificial intelligence, the psychology of human cognition, and list processing" (Retrieved from the ACM website: http://awards.acm.org/citation.cfm?id=3167755&srt=all&aw=140&ao=AMTURING&yr=1975).

APPENDIX G

PUBLICATION PRACTICES IN COMPUTER SCIENCE

At the onset of this study, I expected academic computer scientists to approximate the norms of science by publishing in archival[207] journals and other publications catalogued by the *Web of Knowledge* (formerly the Institute for Scientific Information [ISI] *Web of Science*). However, when I came across the data collected for this project and another study undertaken by Dr. Mary Frank Fox on productivity in science and engineering, the prevalence of publications in conference proceedings among computer scientists was notable and had to be explained. Personal consultations with computer science faculty (conducted in the Fall of 2010 with three faculty members from the Georgia Tech Departments of Electrical and Computer Engineering [ECE] and Computer Science) as well as Computing Research Association (CRA) publications (Patterson, Snyder, & Ullman, 1999; Pollack & Snir, 2008) revealed that many computer science faculty publish in conference proceedings (and some write technical reports) and that these publications are counted toward promotion (although additional qualifications consisting of what are the top conferences and awards in one's area of research are needed for evaluation).

The inquiry into the issue of publications uncovered an ongoing debate about the use of journal publications in evaluations of computer scientists. Computer science faculty can be divided into theoreticians and experimentalists on the basis of their research; theoreticians write papers and experimentalists conduct research involving computational artifacts and are more likely to publish in conference proceedings (Patterson, Snyder, & Ullman, 1999, p. A). As a result, the CRA claimed that "relying on

[207] "An archival journal is a scholarly periodical that publishes original and significant papers that have lasting value to its field. It is a journal of record that researchers can go back to, years later. Libraries generally keep back issues of archival journals even when they might discard other publications such as conference proceedings. The papers submitted to an archival journal are formally evaluated by referees appointed by the journal's editor. The referees are expected to consider not only the originality and significance of each submission, but also its soundness and technical accuracy" (Abrahams, 1988, p. 370). Archival journals as a term is used to differentiate these academic journals from "read and through away" journals.

journal publications as the sole demonstration of scholarly achievements, especially counting such publications to determine whether they exceed a prescribed threshold, ignores significant evidence of accomplishment in computer science and engineering" and "handicaps their [faculty] career, and indirectly harms the field" (Patterson, Snyder, & Ullman, 1999, p. A). Career obstacles and evaluation problems of experimental computer science and engineering (ECSE) faculty were also addressed by the National Research Council (NRC) (1994) and in some research institutes (Liskov, 1992). The committee looking into this issue found that "publication practices in ECSE emphasize conference publications over archival journal publications, a fact likely to be negatively interpreted by the 'paper counters' of university promotion and tenure committees" (NRC, 1994, p. 60). It also acknowledged ambiguity about what constituted a scholarly work within computer science and engineering. The contributions of the ECSE faculty involve building systems, software, and other artifacts. In addition to publications, ECSE faculty may disseminate information about their artifacts by holding demonstrations or making artifacts available for download on their websites. Refereed archival journals are not always preferred means of dissemination because they take more time to appear. Alternative channels, such as leading conferences, are "typically carefully refereed (although by a different process than is used for journals) and have high standards for acceptance, as indicated by relatively low rates of acceptance" (NRC, 1994, p. 65). Most importantly, it takes 6 to 10 times as long for the acceptance of publications and 2.7 to 5 times as long for work to be published in a journal compare to conference proceedings (NRC, 1994, p. 136).

As such, the prevalence of publications in conference proceedings (in the *Web of Knowledge*, conference proceedings are part of the Conference Proceedings Citation Index- Science (CPCI-S) available only from 1990 to present and thus could not be used for this study) and the various means by which experimental scientists claim the benefit of their artifacts (the proofs of the performance, the concept, and existence of their artifacts [NRC, 1994]), render the productivity measures based solely on the publication rate of articles potentially incomplete. In addition, poor predictive power of the impact measure (highest citation count) could be explained by heterogeneity and fragmentation in the field. Future research should investigate how to account for various forms of contributions and publication practices in computing.

Researchers in computer science have a number of outlets for disseminating their research, including books,[208] web pages, journals in mathematics, physics, engineering (IEEE-CS), and various ACM journals (among others). To examine the accuracy of collected data on publications, I conducted two cross-verifications: 1) I compared publications listed in curriculum vitae (CV) (N=7) found in archives to publication statistics retrieved from the *Web of Science* (Science Citation Index Expanded); and 2) I compared the publications collected through the *Web of Science* (Science Citation Index Expanded) with those in the *IEEE Xplore* database (containing IEEE publications) and the *ACM Digital Library* (containing ACM publications and conference proceedings). In the first case, the differences that I found were very small and the disparities could be accounted for when considering the type of publication listed in *CV* (peer reviewed journals, conference proceedings, other publications). I concluded that the publication statistics used in my study included only peer-reviewed publications, some transactions and some special publications but no conference proceedings. In the second comparison, I found that most of the IEEE publications were included in the *Web of Science*, but the publications in the *ACM Digital Library* were not always included in the *Web of Science* (Science Citation Index Expanded). Turing and control group scientists had more publications in the *ACM Digital Library* than in the *Web of Science* (though when I compared only articles and proceedings, the differences were not great: 91 extra publications for non-Turing scientists and 71 extra publications for Turing scientists). It was evident that not all of the ACM publications were included in the *Web of Science* (Science Citation Index Expanded); some of them might have been part of the Conference Proceedings Citation Index- Science (CPCI-S). Upon close examination, I found that some of the publications from conference proceedings and transactions were also published in ACM journals and were included in the *Web of Science*, which provided

[208] See a note on the impact of books in chapter 6.

additional reasons to use only those publications that passed the criteria for inclusion in the *Web of Science* (Science Citation Index Expanded) database. (Moreover, the *IEEE Xplore* database did not provide citation statistics while the *ACM Digital Library* did not provide citation statistics by year.)

I would have liked to include patent data as an indicator of productivity. However, information on patents was largely incomplete. The United States Patent and Trademark Office (USPTO) Patent Database has a major restriction—inventor names were not searchable for patents filed prior to 1975, thus limiting the capacity to find patents for studied group of computer scientists ("Patents from 1790 through 1975 are searchable only by Issue Date, Patent Number, and Current US Classification."[209]).

[209] From the front page of USPTO database http://patft.uspto.gov/netahtml/PTO/search-adv.htm

APPENDIX H

DOCTORATES AWARDED, BY MAJOR FIELD, 1920-99

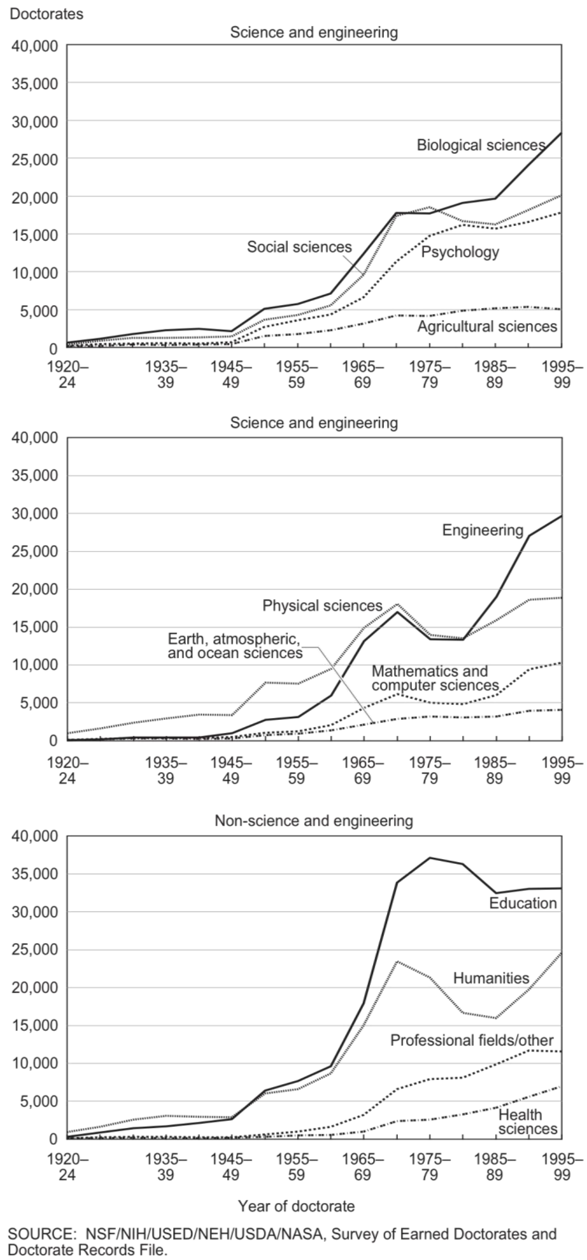

Figure H.1. Doctorates Awarded, by Major Field, 1920-1999

Source: See p. 14 of National Science Foundation [NSF], Division of Science Resources Statistics. (2006). *U.S. Doctorates in the 20th Century* (NSF 06-319, Lori Thurgood, Mary J. Golladay, and Susan T. Hill). Arlington, VA.

APPENDIX I

DEVIATIONS AND IMPORTANCE OF DEGREES

(findings from cases)

Among the 55 Turing Award recipients, three scientists stand out, as they received not one but two advanced (doctoral) degrees. All three scientists are of foreign decent: Edsger Dijkstra was born in the Netherlands and remained Dutch despite later work in the United States; Andrew Chi-Chih Yao was born in China and then immigrated to Taiwan and then to the United States; and Joseph Sifakis was born in Greece but later moved to France. Dijkstra's professional story is widely known. During his studies in physics during the summer of 1951, he took a three-week programming course in electronic computers at Cambridge University, which benefited him the following year when he began working part-time as a computer programmer at the Mathematical Centre in Amsterdam (while still in school). His work at the Centre became the impetus for a second degree in computer science. Thus, a second degree was a "natural" credential showing what he was already doing (research in a new field), which proffered extra marketing value.

Very little is known about the motivations behind Andrew Chi-Chih Yao's decision to switch to computer science after he completed a Ph.D. in physics at Harvard University in 1972. The switch to computer science may indicate a genuine interest in the emerging field, but the reasons why each decided to formalize his new knowledge in the form of a degree are not exactly known (except that it may have been appropriate for a particular academic setting and achievable). The second *doctorat d'état* (Habilitation) degree in mathematics of Joseph Sifakis is easier to explain as it is one of the highest academic qualifications for a scholar in France (and a few other European countries). In his case, the trajectory of moving from research in computer science to contributions in mathematics reminds us of the close connection between the two disciplines.

In contrast to those who pursued advanced degrees, another Turing Award scientist, Robert Floyd, graduated from the University of Chicago in 1953 with a bachelor's degree in liberal arts (when he was only 17) and stayed on for his second bachelor's in physics (graduating in 1958). Having worked with computers and published many “noteworthy” papers, he became an academic professor at such institutions as Carnegie Mellon and Stanford without the credentials of a Ph.D. degree. Donald Knuth, his colleague and close collaborator at Stanford, remarked that “although Floyd never actually obtained a Ph.D., several of his papers were better than any Ph.D. thesis that he saw” (O’Regan, 2008, p. 113). Floyd represented a brilliant exception for whom the usual requirement of a Ph.D. had been lifted.

The case of Dennis M. Ritchie helps us further understand the value of having the “right” credentials. His brief (auto) biography at Bell Labs reads:

> I was born Sept. 9, 1941 in Bronxville, N.Y., and received Bachelor's and advanced degrees from Harvard University, where as an undergraduate I concentrated in Physics and as a graduate student in Applied Mathematics. The subject of my 1968 doctoral thesis was subrecursive hierarchies of functions.[210]

His own statement leads one to believe that he has completed a doctoral thesis. He joined Bell Labs in 1967, and the *Bell Systems Technical Journal* from July-August 1978 listed Ritchie as having the Ph.D. in applied mathematics with a completion date of 1968.[211] However, the record of his Ph.D. dissertation is missing from the ProQuest *Dissertations & Theses* database, and his dissertation cannot be located in the Harvard library search engine. An inquiry sent to the Harvard University Archives, which stores the older theses, resulted in this reply: “The 2005 *Harvard Alumni Directory* does list Mr. Ritchie as a Harvard graduate student from 1965-1968, but the directory does not indicate that he obtained a Ph.D. degree” (Harvard University Archives Reference Staff, personal communication, January 3, 2011). The actual explanation turned out to be simple: Ritchie did not finish the degree. He did spend about four years in graduate school working on a thesis of recursive functions and participating in other projects. When confronted with a question of graduate education in an interview by Robert Slater, Ritchie brushed it off, “I was so bored, I never turned it [his thesis] in” (1987, pp. 276-277). As

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210 “Dennis M. Ritchie.” (n.d.) Retrieved from http://cm.bell-labs.com/cm/cs/who/dmr/bigbio1st.html (2011, Jan. 16).

211 For example, see his entry in the *Who’s Who in Science & Engineering* (2006-2007), 9th ed.

the plethora of printed and online sources continue to propagate, he never bothered to correct the simple fact that he actually did not complete a Ph.D.[212]

Is it that important that Ritchie did the research but never satisfied the formal requirements of a Ph.D. degree? The heroic tale of Ritchie's achievements is not written by him but by the public, which in some way absolves him of any wrong doing (besides being deceptive).

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[212] See http://www.cs.wlu.edu/~whaleyt/classes/313/Turing/Jaschob-Ritchie-Thompson.html; http://www.sciencedaily.com/releases/1998/12/981208172703.htm. (What exactly did they mean by "completed a Ph.D. thesis"?); http://everything2.com/title/Dennis+Ritchie; Warford, S. J. (2009). Computer Systems (4th ed.). Sudbury, Mass.: Jones and Barlett Publishers (p. 460). Deitel, H. M., Deitel, P. J. & Choffnes, D. R. (2003). Operating Systems (3rd ed.). Upper Saddle River, NJ: Prentice Hall.

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